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Lien Lamey, Barbara Deleersnyder, Marnik G. Dekimpe, &
Jan-Benedict E.M. Steenkamp

How Business Cycles Contribute to Private-Label Success: Evidence from the United States and Europe

The growth of private labels over the past decades has been attributed to various factors. This article formally addresses the link between private-label success and economic expansions and contractions using recently developed time-series/econometric techniques. The findings confirm conventional wisdom that a country's private-label share increases when the economy is suffering and shrinks when the economy is flourishing. However, asymmetries are found in the extent to and speed with which private-label share changes in cyclical up- versus downturns. Consumers switch more extensively to store brands during bad economic times than they switch back to national brands in a subsequent recovery. In addition, the switch to private-label brands is faster than the opposite movement to national brands after the recession ends. Finally, not only are consumers more prone to buy private labels during economic downturns, but some keep buying them when bad economic times are long over as well, leaving permanent "scars" on national brands' performance level. The authors argue that national-brand manufacturers can mitigate the effect of an economic downturn on their shares by intensifying their marketing-support activities in recessions. Such a proactive strategy is not often observed. On the contrary, available evidence suggests that many manufacturers exacerbate their predicament by cutting back on their marketing expenses when the economy turns sour. Most retailers invest more strongly in their private-label program when the economy deteriorates, making it even more difficult for national brands to catch up with the share lost during contractions.

Private-label products now account for more than 20% of global grocery sales and are expected to grow to 30% by 2020 (M+M Planet Retail 2004). Although considerable cross-country differences still exist—a 2003 ACNielsen survey reports an aggregate private-label share of approximately 15% in the United States, which is below the level in many Western European countries, such as Switzerland (38%), Spain (23%), and France (21%)—all developed countries have witnessed a steady increase in the share commanded by store brands over the past decades. In the United Kingdom, for example, private-label share rose from 21.5% in 1980 to 39.3% in 2003, and Belgium witnessed a growth from 11.4% in 1983 to 30.1% in 2003. This growing success poses a serious challenge to manufacturers of consumer goods and has been attributed to factors such as a gradual shift in the communication budget from advertising to sales promotions (Hoch, Montgomery, and Park 2002), the growing concentration in the retail sector (Hoch and Banerji 1993), an improvement in the quality of private labels over time (Steenkamp and Dekimpe 1997), and the increasing efforts that retailers put into their private-label programs (Hoch 1996).

Various authors have also linked private-label performance to economic conditions. For example, Quelch and Harding (1996, p. 99) observe that "private-label market share generally goes up when the economy is suffering and down in stronger economic periods." Likewise, Nandan and Dickinson (1994) state that during difficult economic times, the popularity of private labels tends to increase, whereas in periods of relative economic prosperity, the share of national brands increases. A similar feeling is echoed in many business reports. A Deloitte & Touche (2003, p. 2) report argues that "private labels have typically experienced significant growth in times of recession, due to their low prices, and the reduced disposable income of households." This does not bode well for national-brand manufacturers. Unlike other drivers of private-label success, the general economic conditions are largely beyond their control. It is possible, however, that the opposing effects during contractions and expansions will cancel out each other. However, some sources have speculated that despite economic recov-

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ery, legions of consumers are not willing to switch back to manufacturer brands, even when they can again afford them (*The Wall Street Journal* 1993). If this pattern is systematic, the sequence of recessions and expansions would contribute to the prolonged upward evolution in private-label share over repeated business cycles.

Furthermore, is the rate of change in private-label share symmetric across expansion versus contraction periods? For example, do grocery shoppers quickly switch to less expensive private-label brands as the economy deteriorates, and are they more hesitant to switch back to national brands when economic prospects begin to improve? Such an asymmetric pattern would be the net result of actions by individual consumers, retailers, and/or manufacturers in response to aggregate economic fluctuations.

The purpose of this article is to shed light on these issues by formally investigating the relationship between private-label success and the aggregate business cycle. Specifically, we address the following three key research questions:

1. Does private-label success behave countercyclically?
2. Does private-label performance behave differently (asymmetrically) over expansion and contraction periods?
3. Does the aggregate business cycle contribute to long-term private-label success?

Our empirical analysis encompasses four countries: Belgium, the United Kingdom, the United States, and West Germany. These countries tend to follow clearly different private-label strategies, ranging from a focus on discount private labels in Germany to a highly sophisticated, three-tier private-label strategy in the United Kingdom, with Belgium and the United Sates in between (Kumar and Steenkamp 2006). The international setting contributes to the empirical generalizability of the results (Steenkamp 2005).

We organize the remainder of this article as follows: First, we review the literature on the relationship between private-label success and economic conditions. Second, we develop a framework for understanding the impact of business cycles on private-label share. Third, using this framework, we develop predictions about the effect of business-cycle fluctuations on private-label performance. Fourth, we describe the methodology and the data, followed by the empirical results. Finally, we present managerial implications and suggestions for further research.

Previous Research

Some prior literature has already suggested that there is a negative link between private-label success and the business cycle. Quelch and Harding (1996) note that U.S. private-label success increased remarkably during the 1981–1982 economic recession. During that period, U.S. private-label share peaked at 17%, compared with 14% during the previous years. In a study of the impact of the recent Asian economic crisis, Ang, Leong, and Kotler (2000) observe an increasing trend toward buying store brands during a recession. In the only quantitative study to date, Hoch and Banerji (1993) conclude that in the United States, variation in private-label share is closely linked to the business cycle. Using annual data from 1971 to 1993, they find that changes in aggregate private-label share are negatively related to changes in disposable income.

Our study extends previous work in several important ways. First, to the best of our knowledge, no study has systematically analyzed the relationship between private-label share and the economy from a business-cycle perspective. Existing knowledge of this relationship is often limited to the analysis of a single recession period (e.g., Ang, Leong, and Kotler 2000), which does not allow for rigorous conclusions. Only Hoch and Banerji (1993) examine a longer time span, covering multiple contraction and expansion phases. However, they emphasize the short run rather than the business-cycle relationship. They difference their data before regressing private-label share on disposable income. The first-difference filter reweights strongly toward the higher frequencies (associated with short-term fluctuations) and downweights lower frequencies that are typically associated with business-cycle fluctuations (Baxter and King 1999).

Second, unlike prior work, we do not presume that private-label performance reacts to the same extent and with the same speed to increases and decreases in economic activity. We explicitly allow for asymmetric performance in economic up- and downward periods.

Third, although several academic and business writers have theorized that private labels grow in economic downturns, no study has formally investigated the extent to which this increase is cancelled out in the subsequent recovery period or whether part of it is permanent. This is another key question of interest to both national brand manufacturers and retailers.

Thus, to study the link between private-label success and the general state of the economy, we (1) apply a business-cycle filter to the data to analyze the extent of comovement between private-label share and the aggregate business cycle over repeated recession and expansion periods; (2) consider the potentially asymmetric nature of this relationship; (3) explore the presence of permanent upward shifts in private-label performance due to business cycles; and (4) do this for several key private-label countries, broadly covering the range of private-label strategies followed in the marketplace. These issues have not been comprehensively analyzed in previous research, but they are significant to both manufacturers and retailers.

Cyclical Sensitivity of Private-Label Share

We propose a framework to understand the cyclical sensitivity of private-label share to business-cycle fluctuations. Our framework distinguishes between four major components of cyclical fluctuations—cyclical comovement, deepness asymmetry, steepness asymmetry, and asymmetric growth—and three marketplace parties—consumers, national-brand manufacturers, and retailers.

"Cyclical comovement" refers to the extent to which fluctuations within private-label-share series behave in step, or comove, with the country's aggregate business cycle. Three types of cyclical comovement may exist (Stock and

Watson 1999): procyclical (movement in the same direction as the aggregate economy), countercyclical (movement in the opposite direction), and acyclical (no comovement). Moreover, economic studies have found cyclical fluctuations in macroeconomic aggregates, such as gross domestic product (GDP) (Razzak 2001), unemployment (Bodman 2001), and consumption (Holly and Stannett 1995), to behave asymmetrically across expansion versus contraction periods. Two kinds of cyclical asymmetries are distinguished: deepness asymmetry and steepness asymmetry (Sichel 1993). "Deepness asymmetry" pertains to the phenomenon that the deepness of series' troughs may differ from the height of their peaks over business-cycle periodicities. "Steepness asymmetry" refers to asymmetry in the speed of adjustment, in that series drop faster (or slower) than they increase over business-cycle periodicities. We explore whether analogous asymmetries are present in private-label share.

Even if deepness and/or steepness asymmetries are present across expansion and contraction periods, the question remains regarding the extent to which private-label-share gains during a contraction are permanent, leaving a permanent scar on national brands' performance, or whether the economic recovery is strong/long enough for the latter to recoup fully. We estimate an asymmetric growth model (Beaudry and Koop 1993; Cover 1992) to investigate whether cyclical shocks cause only temporary deviations around an underlying trend driven by other factors (e.g., a gradual increase in the private labels' quality, the growing concentration in the retail industry, an expansion in the number of chains and product categories carrying private labels; see, e.g., Kumar and Steenkamp 2006) or whether these cyclical disturbances alter the private labels' long-term growth path, with a differential persistent impact for expansion and contraction periods.

We use these four components to understand how consumers' (demand side) and manufacturers' and retailers' (supply side) responses to aggregate business-cycle fluctuations may result in predictable effects on private-label sales. We believe that this framework provides a useful tool for developing predictions about the impact of business-cycle fluctuations on private-label share. Note that we test the expected pattern of variation in private-label share rather than the psychological and managerial processes that give rise to these predictions.

Demand Side: Consumer Purchase Adjustment over the Business Cycle

Cyclical comovement. As consumers' abilities and willingness to buy goods decrease during economic contractions, they may want to economize on their expenditures by reducing the quantity bought or by postponing their purchases until prospects become better (Katona 1975). This strategy is less of an option for consumer packaged goods (CPGs) because of their more necessary nature. To save on CPG purchases, consumers are more likely to economize on price (Shama 1981). Given that, on average, store brands are priced 25%–30% below national brands (e.g., Kumar and Steenkamp 2006), they become an obvious candidate to switch to when the economy turns sour. This behavior is expected to lead to countercyclical movements in private-label share, which is consistent with the finding that the propensity to buy private labels is inversely related to income (Ailawadi, Neslin, and Gedenk 2001). Moreover, during economic slowdowns, consumers become more inclined to acquire price information (Wakefield and Inman 1993), making them more price conscious (Estelami, Lehmann, and Holden 2001). Because price consciousness has been found to be a good predictor of private-label success (Ailawadi, Neslin, and Gedenk 2001), this further increases the countercyclical behavior of private-label share.

Cyclical asymmetries. At the beginning of a recession, consumers have a strong incentive to limit their spending and wait for better times (Gale 1996). This is enhanced by the notion that people lose their trust and confidence in the economy relatively quickly, which has been found to be a strong predictor of purchase-adjustment decisions (Allenby, Jen, and Leone 1996). Accordingly, consumers' willingness to buy premium-priced national brands is expected to decrease sharply at the onset of a recession.

Consumers may continue to economize on their expenditures even if the economic climate begins to improve again, resulting in a slower return to national brands in the subsequent expansion. This delayed reverse movement may emerge because (1) consumers typically find themselves at the lowest level of their actual income or ability to buy right after the downturn (Gale 1996); (2) any initial rise in their income may be used to pay off debts and rebuild a precautionary stock of assets or capital (Carroll 1992); and (3) the general pessimism regarding the recent recession and their breach of trust has made consumers more prudent in updating their income expectations, so that the anticipated increase in their future income and wealth remains conservative (Katona 1975). Indeed, it is a well-known principle that has been observed in areas ranging from economics to interorganizational relationships that it takes much less time to breach trust than to restore it (Katona 1975; Nooteboom, Berger, and Noorderhaven 1997). The old adage "once bitten, twice shy" applies here too.[1] This gradual return to national brands during expansions, together with the sharp decrease in the willingness to buy national brands during contractions, results in asymmetric steepness.

Furthermore, people change their purchase behavior more drastically in response to a contraction than to an expansion (Bowman, Minehart, and Rabin 1999). In this vein, we expect that the switch to private labels during the recession will be stronger or more extensive than the subsequent return to national brands in an expansion period, resulting in higher peaks than troughs in the cyclical pattern of private-label share (i.e., deepness asymmetry).

Asymmetric long-term growth. Overall, the aforementioned factors contribute to a pattern in which consumers switch quickly and more strongly to private labels during contractions but return to national brands more gradually in subsequent expansions. However, will all consumers eventually switch back to national brands, resulting in the absence of a long-lasting impact of an economic downturn?

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[1] We thank an anonymous reviewer for this suggestion.

After all, the presence of steepness and deepness asymmetry is not a sufficient condition for such a permanent effect to occur (Beaudry and Koop 1993).[2] If expansions last longer than contractions, national brands might still recover fully and regain their precontraction market share.

However, we expect that a full recovery is not likely, because the perceived quality of private labels is typically lower than their actual quality (Kumar and Steenkamp 2006; Richardson, Dick, and Jain 1994). As we argued previously, an economic recession induces several national-brand buyers to switch to a private label. From actual product experience, which is the most important source of information for consumers to form their quality perceptions (Steenkamp 1989), they may learn that actual private-label quality exceeds their prior perceptions. On the basis of consumers' positive experiences with private labels, we expect that some will not switch back to national brands after the recession, giving rise to a permanent, positive effect of an economic contraction on private-label performance. In a similar vein, Ailawadi and Keller (2004) argue that if store brands can change consumers' quality perceptions (e.g., through direct consumption experience), they will gain more customers, and it will be difficult for manufacturers to win them back.

Supply Side: Manufacturer and Retailer Behavior over the Business Cycle

Cyclical comovement. Manufacturer and retailer actions may reinforce consumers' tendencies to switch to private labels during contractions. Most manufacturers decrease their brand support during bad economic times (e.g., Srinivasan, Rangaswamy, and Lilien 2005). Moreover, manufacturers are loath to reduce prices in a recession (Backus and Kehoe 1992; Deleersnyder et al. 2004), even though price sensitivity is higher at such a time (Estelami, Lehmann, and Holden 2001). This behavior may contribute to the countercyclical behavior in private-label share.

Conversely, retailers tend to rejuvenate their own label when the economy sours (Hoch 1996). When the economy softened in the early 1980s and again at the beginning of the 1990s, numerous U.S. supermarkets revamped their private-label programs with new logos, new items, and more shelf space (Hoch 1996). Similar patterns have been observed in Europe (Walters 1994) and Asia (Davies 2000). Through such countercyclical private-label-support activities, retailers contribute to the countercyclical performance of store brands.

Cyclical asymmetries. Prior research has found that firms adjust their business strategies asymmetrically over different business-cycle phases (Mascarenhas and Aaker 1989). Brand support tends to be cut more quickly during recessions than it is restored when good economic times arrive again (Axarloglou 2003). Prices have also been found to be more flexible going up than going down (Ball and Mankiw 1994) and to be higher during contractions than during expansions (Backus and Kehoe 1992; Deleersnyder et al. 2004). As a consequence of such asymmetric manufacturer and retailer behavior, consumers' switch to private labels during the recession will be faster and more extensive than their subsequent return to national brands in an expansion period. This results in steepness and deepness asymmetry patterns in private-label share.

Asymmetric long-term growth. It is less clear whether long-term growth is also related to manufacturer and retailer actions. Even when manufacturers and retailers adjust their business strategies significantly and asymmetrically over different business-cycle phases, it is unclear whether brand manufacturers can regain lost ground by ramping up marketing investments in economic expansions or whether their retrenchment during recessions generates a decline in expertise (e.g., in research and development) that they cannot fully recoup during the subsequent expansion (Fatás 2002; Hillier and Baxter 2001).

Table 1 summarizes the expected effect of demand- and supply-side behavior on private-label performance along the four cyclical characteristics: nature of the comovement, deepness and steepness asymmetry, and asymmetric growth. Although it would be of interest to quantify the impact from each of the preceding members separately, it is

TABLE 1
Framework to Relate the Business Cycle to Private-Label Share

	Determinants of Private-Label Share			
	Demand Side	Supply Side		Net Effect on Private-Label Share
Business Cycle	Consumer	Manufacturer	Retailer	
Cyclical Comovement[a]	–	–	–	–
Cyclical Asymmetries				
Deepness asymmetry	+	+		+
Steepness asymmetry	+	+		+
Asymmetric Growth				
Contraction	++			+
Expansion	–			

[a] A negative sign means that private-label share is expected to behave countercyclically.

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[2] As we discuss in more detail in the "Methodology" section, deepness and steepness asymmetry refer to the nature of the cyclical fluctuations around private labels' overall trend, whereas asymmetric growth models test whether economic contractions and expansions alter the growth rate of that trend.

important to understand first the overall net impact of the aggregate business cycle on private-label share.

Methodology

Our research methodology consists of four steps. First, we apply the well-known Hodrick and Prescott (1997) filter (hereinafter, the HP filter) to isolate the cyclical component in the various time series of interest. Second, we quantify the extent of cyclical sensitivity in private-label success through the cyclical comovement elasticity. Third, we derive statistics to test for deepness and steepness asymmetry. Fourth, we assess whether expansion and contraction periods affect the long-term growth rate in private-label share differently.

Extracting the Cyclical Component

Not all over-time variation present in a series can be attributed to business-cycle movements. Therefore, in line with economic studies (e.g., Cook 1999; Holly and Stannett 1995), we adopt the HP filter to extract from each individual series the fluctuations that occur at business-cycle periodicities. The HP filter decomposes a time series, y_t, into a trend component, y_t^l, which varies smoothly over time, and a cyclical component, y_t^c, by fitting a smooth curve through a set of data points. The variance of the cyclical component is minimized subject to a penalty for variation in the second difference of the trend component. The cyclical component, which fluctuates around that trend, is then obtained by subtracting the long-term trend from y_t—that is, $y_t^c = y_t - y_t^l$. More formally, the HP filter obtains y_t^l by minimizing

$$(1)\qquad \sum_{t=1}^{T}(y_t - y_t^l)^2 + \lambda\sum_{t=2}^{T-1}[(y_{t+1}^l - y_t^l) - (y_t^l - y_{t-1}^l)]^2,$$

where λ is a penalty parameter that determines the degree of smoothing; the larger its value, the smoother is the resulting growth component. Because business cycles are of varying length that tend to last no longer than eight years (Christiano and Fitzgerald 1998), we choose our smoothing constant to generate a trend that accounts for all fluctuations longer than eight years. We follow the work of Baxter and King (1999), who recommend a value of λ equal to ten for annual series. This value produces a good correspondence between the HP filter and an ideal band-bass filter that passes through cycles between two and eight years. Furthermore, to enhance the comparability across series, we analyze y_t in logarithms, so that the units of y_t^c, when multiplied by 100, represent percentage deviations from the series' growth path (Stock and Watson 1999).

The proposed HP filter has several attractive features. First, the HP filter does not induce any asymmetries in the cyclical component when they were absent in the original series (Sichel 1993). This is a necessary property when exploring the presence of cyclical asymmetries (see the "Quantifying the Extent of Cyclical Sensitivity" subsection). Second, because it removes a stochastic trend from a series, the HP filter induces stationarity in a series that is originally difference stationary (Baxter and King 1999; Holly and Stannett 1995). This avoids the well-known spurious-correlation problem when correlating integrated variables. Finally, the HP filter can be regarded as a special case of a structural time-series model that consists of a trend and a cyclical component. This property will prove to be useful in our validation exercises when we want to control for a potential break caused by the German reunification in 1990 (for details, see Appendix A).

Nevertheless, as with any business-cycle filter, the HP filter suffers from some drawbacks. First, it is unable to distinguish short-term from business-cycle fluctuations (Canova 1998; Reeves et al. 2000). Indeed, the HP filter is a high-pass filter, in that it filters out fluctuations with small frequencies. Because business cycles tend to have a periodicity between two and eight years (Christiano and Fitzgerald 1998), band-pass filters, which can filter out both high and low frequencies, may seem better suited. However, with annual data (as we use), band-pass and high-pass filters become equivalent (Baxter and King 1999) because the Nyquist frequency (i.e., the highest frequency about which there is direct information) then corresponds to a component of two years (Granger and Hatanaka 1964). Second, it has been argued that the HP filter may (as do many other filters) induce spurious cycles within a series, thus causing spurious cross-correlations among filtered series (Harvey and Jaeger 1993). However, in an extensive simulation study, Kaiser and Maravall (1999) find that this problem is very small in HP-filtered series. Third, it has been argued that the results may be sensitive to the choice of smoothing parameter λ (Kaiser and Maravall 2001, p. 116). Thus, we conduct an extensive robustness analysis with other values that have been suggested in the literature.

Quantifying the Extent of Cyclical Sensitivity

To quantify the extent of cyclical sensitivity in private-label success, we derive the cyclical comovement elasticity. We regress the cyclical component extracted from a country's private-label share, pls_t^c, on the corresponding cyclical component filtered from that country's GDP per capita, $gdpc_t^c$. Although, strictly speaking, the business cycle is defined in terms of the joint movement of several economic series across multiple sectors (see www.nber.org/cycles.html), fluctuations in aggregate output have been found to be at the core of the business cycle, making it a good proxy for the country's economic activity as a whole (Stock and Watson 1999, p. 15). This results in the following test equation:

$$(2)\qquad pls_t^c = \beta gdpc_t^c + \varepsilon_t,$$

Because both cyclical components are expressed in percentage deviations, the resulting parameter β is an elasticity estimate.[3] The sign and significance of β indicate whether private-label share evolves pro-, counter-, or acyclical. Conversely, its magnitude reflects the extent to which fluctuations in the general economy are attenuated or amplified in private-label share. The HP filter may induce serial correlation in the data (Engle 1974). To account for this, we can add autoregressive error terms in estimating Equation 2, the number of which we determine on the basis of information criteria (Judge et al. 1988).

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[3] It is not necessary to include an intercept, because both the private-label-share and the GDP-per-capita series are zero-reverting after filtering. We thank an anonymous reviewer for bringing this to our attention

Examining the Presence of Deepness and Steepness Asymmetry

To test whether private-label share displays cyclical (a)symmetries, we explore whether the filtered pls_t^c series is positively skewed or, in other words, skewed to the right.[4] In the case of deepness asymmetry, we expect that the positive deviations from the mean or trend during contraction periods are larger in absolute value than the negative deviations during expansion periods, whereas the number of observations above the mean or trend is smaller than the number below. Similarly, if a time series exhibits steepness asymmetry, its first difference, representing the slope or rate of change, will exhibit positive skewness. As such, increases in the series' growth corresponding to contractions should be larger, but less frequent, than the more moderate decreases during expansions.

To identify potential asymmetries in the evolution of private-label success over contraction and expansion periods, we adopt the nonparametric triples test that Randles and colleagues (1980) propose. In this test, all possible triples (y_i, y_j, y_k) of observations of a series y_t are considered. For a series with T observations, $\binom{T}{3}$, such triples can be identified. A triple is a right (left) triple when the middle observation is closer to the smaller (larger) observation than to the larger (smaller) observation. In a symmetric distribution, there are as many right as there are left triples. If there are relatively more right triples, the underlying distribution is skewed to the right. Formally, the triples test statistic is given by

$$(3)\qquad \frac{\hat{\eta}}{\sqrt{\dfrac{\hat{\sigma}_{\eta}^2}{T}}},$$

where $\hat{\eta} = \dfrac{[(\text{number of right triples}) - (\text{number of left triples})]}{\left[3\binom{T}{3}\right]}$,

which can be shown to equal

$$(4)\qquad \hat{\eta} = \binom{T}{3}^{-1} \sum_{i<j<k} \{[\text{sign}(y_i + y_j - 2y_k)$$
$$+ \text{sign}(y_i + y_k - 2y_j) + \text{sign}(y_j + y_k - 2y_i)]/3\},$$

and

$$(5)\qquad \frac{\hat{\sigma}_{\eta}^2}{T} = \frac{1}{\binom{T}{3}} \sum_{c=1}^{3} \binom{3}{c}\binom{T-3}{3-c}\hat{\varsigma}_c.$$

We refer to Appendix B for the derivation of $\hat{\varsigma}_c$. The asymptotic distribution of the test statistic is standard normal, so we can use conventional critical values. In case of deepness asymmetry, we expect a right-skewed distribution, reflected in a positive value of the triples test statistic, for pls_t^c. As for steepness asymmetry, we derive a comparable asymmetry statistic on the first difference of pls_t^c, Δpls_t^c. Again, a right-skewed distribution will be reflected in a positive test statistic.

Following previous research (see, e.g., Bodman 2001; Cook 1999; Deleersnyder et al. 2004; Sichel 1993), we apply the univariate asymmetry tests to pls_t^c (or Δpls_t^c for steepness asymmetry). As an alternative approach, we could consider using the forecasted values of Equation 2 (i.e., $\hat{\beta}\, gdpc_t^c$) as input to the triples test. However, this procedure suffers from two deficiencies. First, it ignores that $gdpc_t^c$ is a valid but imperfect indicator of the business cycle. As such, $\hat{\beta}\, gdpc_t^c$ may not capture all fluctuations in private-label share that can be attributed to the business cycle. Second, this procedure assumes that the third-moment (skewness) properties of $gdpc_t^c$ automatically pertain to the private-label series as well because a linear transformation (rescaling) of $gdpc_t^c$ cannot alter the presence/absence of asymmetries (Sichel 1993). This assumption appears unduly restrictive. Indeed, prior research has established that several economic variables (e.g., unemployment, industrial production, consumer price level) that are conceptually linked to the business cycle have third-moment properties that differ from those in GDP (Bodman 2001; Sichel 1993; Verbrugge 1998).

Assessing the Presence of Asymmetric Growth

Univariate deepness and steepness asymmetries describe the behavior of the cyclical fluctuations around the series' overall trend or mean level and are studied on the filtered series, that is, where the underlying trend (mean) has been removed. As such, they cannot address whether this differential behavior also contributes to long-term private-label success (e.g., by altering the series' growth rate) or whether they represent only temporary deviations from the underlying trend or mean that eventually cancel out one another (Beaudry and Koop 1993). For example, if all customers who switched to private labels during the contraction would gradually return to buying national brands after the economy recovers, no long-term growth would be observed that could be attributed to the contraction. As such, deepness and steepness asymmetries can exist "with or without there being asymmetry in persistence" (Beaudry and Koop 1993, p. 151).

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[4] In line with prior studies in the economics literature (Bodman 2001; Cook 1999, Razzak 2001), we use a univariate detrending procedure (i.e., the HP filter) to derive the cyclical component, from which we subsequently assess the skewness. Although more complicated multivariate procedures have also been used in prior studies, Canova (1998) finds that the third moment (reflecting the skewness) is not sensitive to the choice of detrending method, and he cautions against the use of multivariate detrending procedures that impose additional restrictions (e.g., common stochastic or deterministic trends) that are not satisfied in the data. In unreported analyses, we found that the various private-label series have a unit root but are not cointegrated with the GDP-per-capita series.

To assess formally whether cyclical shocks affect the private labels' long-term growth and to check whether this effect differs for contraction and expansion periods, respectively, we specify an asymmetric growth model. In line with the work of Beaudry and Koop (1993), Cover (1992), and Thoma (1994), we define two new variables that reflect the general state of the economy at a certain point in time t:

$$(6)\qquad \text{exp}_t \begin{cases} = \text{gdpc}_t^c - (\text{prior trough in gdpc}^c), & \text{if } \Delta\text{gdpc}_t^c > 0 \\ = 0, & \text{if } \Delta\text{gdpc}_t^c \leq 0 \end{cases},$$

and

$$\text{contr}_t \begin{cases} = 0, & \text{if } \Delta\text{gdpc}_t^c > 0 \\ = (\text{prior peak in gdpc}^c) - \text{gdpc}_t^c, & \text{if } \Delta\text{gdpc}_t^c \leq 0 \end{cases}.$$

Decreases (increases) in the cyclical component of GDP per capita correspond to contractions (expansions). The variable exp_t measures the magnitude of the expansion by calculating how much the business cycle, reflected in the filtered GDP-per-capita series, has increased relative to its previous trough. Similarly, the variable contr_t measures the magnitude of a contraction by calculating how much the business cycle has dropped relative to its previous peak when the economy is on a downturn.[5] Private-label growth, Δpls_t, is subsequently linked to current and lagged values of exp_t and contr_t. By assessing whether they have additional explanatory power over lagged growth terms Δpls_{t-j} ($j = 1, \ldots, J$), we test whether the business cycle Granger (1969) causes private-label growth:

$$(7)\qquad \Delta\text{pls}_t = \alpha + \sum_{j=1}^{J}\beta_j\Delta\text{pls}_{t-j} + \sum_{k=0}^{K}\varphi_k^-\text{contr}_{t-k} + \sum_{l=0}^{L}\varphi_l^+\text{exp}_{t-l} + \varepsilon_t,$$

with lag lengths J, K, and L determined on the basis of information criteria (Judge et al. 1988).[6] Note that our asymmetric growth model is specified in differences. Preliminary unit-root tests can be used to determine whether the series is indeed nonstationary (as implicitly assumed in Equation 7). If not, no long-term effects can be detected. However, because the presence of a unit root is a necessary but not sufficient condition for (cyclical) shocks to have a long-term impact (Dekimpe and Hanssens 1995), we still need to test for the significance of $\Sigma_{k=0}^{K}\varphi_k^-$ ($\Sigma_{l=0}^{L}\varphi_l^+$) in Equation 7. Through the intercept α, we control for unobserved factors, such as the gradual increase in private-label quality over time.[7]

By splitting the business cycle into two phases, we test for asymmetries in the long-term response of private-label growth to expansions and contractions. Thus, the effect of a recession is not necessarily cancelled out in a subsequent expansion. Unlike Equation 2, we no longer assess the linkage between the cyclical movements in private-label share, pls_t^c, or the cyclical movements in the economy as a whole. Instead, we now test whether changes in the latter contribute to the private labels' market-share growth (and, thus, their long-term level). The sum of the parameters φ_k^- (φ_l^+) associated with recessionary (expansionary) periods—that is, $\Sigma_{k=0}^{K}\varphi_k^- = \varphi_{ST}^-(\Sigma_{l=0}^{L}\varphi_l^+ = \varphi_{ST}^+)$—gives the combined short-term impact on private-label growth. Because Equation 7 contains lags of the dependent variable, we can show that the impact on the series' long-term or steady-state growth rate becomes, respectively (Franses 2005),

$$\frac{\sum_{k=0}^{K}\varphi_k^-}{1-\sum_{j=1}^{J}\beta_j}(= \varphi_{LT}^-) \text{ and } \frac{\sum_{l=0}^{L}\varphi_l^+}{1-\sum_{j=1}^{J}\beta_j}(= \varphi_{LT}^+).$$

We can derive standard errors of these ratios using the well-known delta method. Under the assumption that a contraction period stimulates private-label growth, we expect that its impact is positive; thus, $\Sigma_{k=0}^{K}\varphi_k^- > 0$. When the impact of an expansion on private-label growth is negative—thus, $\Sigma_{l=0}^{L}\varphi_l^+ < 0$)—the size of the expansions will determine the extent to which the growth-stimulating effect of previous contractions will be offset.

Data

Annual data on the aggregate value share of private labels in CPGs are provided by ACNielsen for Belgium (1983–2004), by Taylor Nelson Sofres for the United Kingdom (1980–2003), by Selling Area Markets Inc and ACNielsen for the United States (1971–2003),[8] and by GfK for West Germany (1975–2002). The data span 20–30 years, which is comparable in length to other studies on business-cycle sensitivity (e.g., Cook 1999; Mills 2001).

Although private labels have grown their share in total grocery sales in all four countries, there are some notable differences as well, especially in terms of how this growth was obtained (Kumar and Steenkamp 2006). In Germany, to a large extent, private-label growth is driven by the success of the hard-discount format, as implemented by chains such as Aldi, Lidl, and Penny. For example, Aldi sells store brands almost exclusively (>95%) and is one of the fastest-growing retailers in the German grocery market. By 2002, it had already captured close to 18% of total grocery retailing sales in Germany. The absence of manufacturer brands from most hard discounters' assortments leads to an almost unobstructed growth of private labels. In contrast, in the United Kingdom, private-label growth is mainly fueled by retailers' ability to offer an elaborate three-tier private-label range, including value, standard, and premium store brands. Finally, the United States and Belgium (the latter country being similar in private-label landscape to other European countries, such as France, Spain, and the Netherlands) are located in between Germany and the United Kingdom. Their growth in private-label sales can be attributed both to the increasing success of discount operations and to the growing importance of elaborate, quality-oriented, private-label programs by mainstream retailers.

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[5] Through this operationalization, all values for exp_t and contr_t will be nonnegative, making the interpretation of their corresponding coefficients in Equation 7 more straightforward.

[6] For the sake of simplicity, we do not explicitly model that private-label share is bounded between zero and one, because it could be argued that private-label share operates well away from these boundaries. Nonetheless, we obtained the same substantive findings when we replaced Δpls_t by $\Delta[(\text{pls}_t)/(1 - \text{pls}_t)]$ in Equation 7.

[7] For an in-depth discussion on the role of the drift term in unit-root models, see Juselius and Hargreaves (1992).

[8] We are indebted to Stephen Hoch for making the U.S. data available to us.

Data on real GDP per capita are used as a proxy for the general economic activity in a particular country. Business-cycle fluctuations across many sectors are reflected in aggregate output, making the cyclical component of GDP (per capita) a good indicator for the overall economic cycle (Stock and Watson 1999). We obtained GDP per capita, expressed in constant prices, from the United Nations Statistic Divisions for Belgium, the United Kingdom, and the United States. For West Germany, we obtained these data from the VGRDL (Volkswirtschaftliche Gesamtrechnungen der Länder).

Empirical Results

The Extent of Cyclical Sensitivity

To control for serial correlation in the data, we added two autoregressive terms to Equation 2. The Chow test on common slopes and autoregressive error terms revealed that we could pool the four countries in our sample ($F(9, 86) = 1.24$, $p > .10$).[9] We obtained a significant and negative comovement elasticity ($\beta = -.96$, $p < .01$; $R^2 = .42$), indicating that private-label share behaves countercyclically. It increases during contractions and decreases during expansions. This confirms conventional wisdom from a business-cycle perspective and is in line with the negative short-term relationship that Hoch and Banerji (1993) find.

Cyclical Asymmetries

In addition to the extent of cyclical sensitivity in private-label share, we consider the nature of cyclical ups and downs, as reflected in the respective cyclical-asymmetry statistics. The test results for the nonparametric triples test appear in Table 2. To avoid potential distortion that may arise from deriving asymmetry statistics after log-transforming the series (DeFusco, Karels, and Muralidhar 1996), we based all inferences about these univariate asymmetries on the cyclical component extracted from the original (nontransformed) series.[10]

In line with our expectations, cyclical fluctuations in private-label share evolve asymmetrically across expansion and contraction phases. For all countries, the triples test showed the expected positive sign for both deepness and steepness asymmetry, even though the test was significant in few individual cases. However, note that the power of asymmetry tests in business-cycle research has been found to be low, especially when working with annual data (Mills 2001; Razzak 2001). Psaradakis and Sola (2003) show that whenever evidence of asymmetry in the cycle is established using HP-filtered series, this can be taken as strong evidence in favor of asymmetry.

Meta-analysis is a recommended way to address the challenge posed by the low power of individual tests. It offers a more powerful test for the presence of business-cycle asymmetries than do the individual test statistics because it combines evidence from all countries, allowing for an overall significance test. Using the meta-analytic method of adding weighted Zs (Rosenthal 1991), we found support for asymmetric behavior in both the extent (deepness) to which and the speed (steepness) with which private-label share fluctuates over the business cycle (both ps < .05). Thus, these results indicate that increases in

TABLE 2
Results on Deepness and Steepness Asymmetry

	Belgium (n = 22)	United Kingdom (n = 24)	United States (n = 33)	West Germany (n = 28)	Meta-Analysis[a]
Deepness	.050	.043	.039	.033	1.92**
	(1.13)	(1.16)	(.93)	(.76)	
Steepness	.042	.061*	.034	.067*	2.13**
	(.83)	(1.31)	(.74)	(1.50)	

*p < 10 (one-tailed test).
**p < .05 (one-tailed test).
[a]The meta-analysis reports z-values that we obtained by the method of adding weighted Zs (Rosenthal 1991).
Notes: Z-statistics are in parentheses

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[9] Note that the pooling test is conducted on the filtered, rather than the original, series. As such, we account for differences in the long-term growth rates, which may distort the cyclical inferences.

[10] We obtained the same substantive findings when working with log-transformed private-label-share series instead of the original series.

private-label share during economic contractions occur more extensively and faster than declines in private-label share in subsequent expansion phases.[11]

Do Economic Contractions Lead to Permanent Private-Label Growth?

The question still remains whether the net result of a series of cyclical ups and downs evokes long-term private-label growth. To draw this conclusion, (1) the private-label-share series should be evolving, and (2) long-term changes in private-label share should be related to business-cycle swings. Unit-root tests (Enders 1995) indicated that the private-label series are indeed evolving. We could not reject the null hypothesis of the presence of a unit root for any of the four countries (all *ps* > .10).

To determine whether long-term changes in private-label share can be attributed to business-cycle swings, we estimated the asymmetric growth model of Equation 7. Before estimation, a pooling test confirmed that common slopes were allowed ($F(9, 82) = 1.38$, $p > .10$) but that country-specific intercepts were needed ($F(3, 91) = 2.40$, $p < .10$). We subsequently pooled the data across the four countries, including country-specific intercepts. We included one lag for private-label-share growth, but we did not include any lags for real-GDP-per-capita expansion and contraction (thus, in Equation 7, $J = 1$, and $K, L = 0$). We derived standard errors using White's robust covariance estimation method (Greene 2003). The results appear in Table 3.

Three of the country-specific intercepts were significant—$\alpha_{Belgium} = .022$ ($p < .10$), $\alpha_{U.K.} = .012$ ($p < .10$), and $\alpha_{West\ Germany} = .018$ ($p < .05$)—indicating the presence of a positive drift in private-label share. The country-specific intercept for the United States was not significant ($\alpha_{U.S.} = -.003$, $p > .10$). Furthermore, we found that previous-year private-label evolution had a significant, positive impact on private-label evolution this year ($\beta_1 = .34$, $p < .05$).

Most important, we found that economic expansions and contractions affect private-label-share evolution to a different degree. Contractions cause a substantial positive impact on private-label growth that is not offset in subsequent expansions. This important finding applies to changes in both short-term and long-term private-label growth.

Impact on short-term private-label growth. On the basis of Equation 7, we found a negative, albeit insignificant, impact on the trend or growth rate in private-label share during economic expansions ($\varphi^+ = -.18$, $p > .10$), whereas a contraction induced a significant, positive effect on short-term private-label growth ($\varphi^- = .80$, $p < .05$). Because we work in log-log space, these parameters are elasticities. Thus, when GDP per capita decreases 1% compared with the peak just before the recession, private-label growth increases .80% in the short run. Conversely, when GDP per capita increases 1% compared with the trough just before the expansion, private-label growth declines .18% in the short run. In summary, a contraction causes a short-term upward lift in the trend of private-label share, which is (partly) maintained afterward, because this shift is not fully recouped in the subsequent expansion.

Impact on long-term private-label growth. The impact of a recession on the long-term or steady-state growth in private-label share was again positive and significant ($\varphi^-_{LT} = 1.22$, $p < .05$), whereas during the expansion, the long-term growth rate was not significantly affected ($\varphi^+_{LT} = -.28$, $p >$

TABLE 3
Results of the Asymmetric Growth Model

		Estimate	***p* Value**
Country-Specific Drift			
	$\alpha_{Belgium}$	.022	.055[a]
	$\alpha_{U.K.}$	.012	.071[a]
	$\alpha_{U.S.}$	–.003	.666[a]
	$\alpha_{West\ Germany}$	.018	.029[a]
Lagged Private-Label Growth			
	β_1	.34	.023[a]
Business-Cycle Effects			
Contraction			
	φ^-_{ST}	.80	.006[b]
	φ^-_{LT}	1.22	.009[b]
Expansion			
	φ^+_{ST}	–.18	.223[b]
	φ^+_{LT}	–.28	.216[b]
$R^2 = .36$, $N = 98$			

[a]Two-sided *p* value.
[b]One-sided *p* value.

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[11] As a further test for our assertion that the observed asymmetries in pls^c_t are driven by the business cycle, we applied the triples test to the residuals of Equation 2. We found no evidence of any remaining asymmetry in these residuals. Detailed test results are available on request.

.10). Thus, when, in recessionary times, GDP per capita decreases 1% compared with the peak just before the recession, this causes a long-term upward lift in private-label growth of 1.22%. Conversely, when GDP per capita increases 1% compared with the trough just before that expansion, this generates a long-term growth reduction of only an insignificant .28%. Thus, a fraction of the consumers who switched to store brands in a contraction stay with their choice even after the economy improves.

Robustness Checks

Alternative smoothing parameters. We followed the recommendation of Baxter and King (1999) to set λ equal to 10. However, other researchers have recommended smaller values. Canova (1994) considers a value of λ equal to 4, Ravn and Uhlig (2001) suggest a value of 6.25, and Harvey and Jaeger (1993) work with a value of 7. Different values of λ lead to the derivation of slightly different cyclical elements. We conducted extensive robustness analyses to examine the sensitivity of our results to a wide range of λs, namely, the three aforementioned smaller values (4, 6.25, and 7) and the three larger ones (15, 20, and 30). The results (see Table 4) show that our main findings are robust to the choice of the smoothing value.

Alternative filtering approach. Different filtering procedures extract slightly different types of business-cycle information from the original series (Canova 1998). We reanalyzed our data, using another widely used detrending procedure, namely, the band-pass filter of Baxter and King (1999). The results based on brand-pass-filtered data confirmed the findings we obtained from HP-filtered data. The comovement-elasticity results revealed the same general pattern as before; there is combined evidence for countercyclical movement in private-label share ($\beta = -.70$, $p < .01$), and its value closely resembled the value of –.96 we found previously. Moreover, the analyses confirmed the presence of cyclical asymmetries, both in terms of deepness ($p < .05$) and in terms of steepness ($p < .10$). Finally, for the asymmetric growth model, we again obtained in both the short and the long run a significant, positive effect on private-label growth of a contraction ($\varphi^-_{ST} = 1.05$, $p < .01$; $\varphi^-_{LT} = 1.45$, $p < .05$), which was not offset in the subsequent expansion period ($\varphi^+_{ST} = -.11$, $p > .10$; $\varphi^+_{LT} = -.16$, $p > .10$).

Error in the cyclical component. Any filtered series may contain some noise. Different smoothing parameters in the HP filter and alternative filters extract somewhat different business-cycle information from the same series, with different amounts of noise (Kaiser and Maravall 2001). As we reported previously, we replicated our findings with (1) six alternative smoothing values and (2) the band-pass detrending procedure. This gives more confidence in our findings and indicates that error in the extracted cyclical component does not seriously affect our key insights.

Alternative specification of the asymmetric growth model. In estimating the asymmetric growth model (Equation 7), we accounted for the magnitude of expansions and contractions (see Equation 6). We assessed the robustness of our findings to an alternative specification of the expansion and contraction variables, focusing on the occurrence of an expansion or contraction per se rather than on their magnitude. We defined a dummy variable that equals one when the economy is downturning and zero when the economy is expanding.

In the corresponding pooled asymmetric growth model with country-specific fixed intercepts, we again found a positive impact of a recession on private-label-share growth ($\varphi^-_{ST} = .020$, $p < .05$). Because the country intercepts were all positive and significant (except for the United States, in which the intercept was insignificant at the 10% level), we conclude that the additional positive effect found during the contraction is not cancelled out by the subsequent expansion. We also estimated a model without intercepts but with an extra dummy variable to identify expansions. The dummy for recessions was positive and significant, whereas the dummy for expansions was positive but insignificant, leading again to the conclusion that increases in private-label share during recessions are not compensated for in the subsequent expansion. In summary, these alternative model specifications support our finding that the sequence of aggregate business cycles contributes to long-term private-label success.

German reunification in 1990. Germany experienced a major change during the time span under investigation, namely, its reunification in 1990. After the unification, West German investments in production and equipment fell because of major capital transfers to former East German

TABLE 4
Robustness Checks: Different Smoothing Parameters for the HP Filter

	λ = 4	λ = 6.25	λ = 7	λ = 10	λ = 15	λ = 20	λ = 30
Comovement Elasticity	–1.00**	–.98**	–.98**	–.96**	–.94**	–.93**	–.90**
Cyclical Asymmetries[a]							
Deepness	1.76*	1.88*	1.87*	1.92*	1.96*	1.91*	1.84*
Steepness	1.96*	2.07*	1.64*	2.13*	1.95*	1.91*	2.48**
Asymmetric Growth							
β_1	.36*	.46**	.36*	.34*	.44*	.43**	.42**
φ^-_{ST}	.98**	.79*	.89**	.80*	.65*	.56*	.53*
φ^+_{ST}	–.15	–.17	–.11	–.18	–.23	–.25	–.25

*$p < .05$
**$p <$ 01.
[a]We obtained the reported z-values of the meta-analysis by the method of adding weighted Zs (Rosenthal 1991).

regions (Lütkepohl, Teräsvirta, and Wolters 1999). In line with prior studies on the Germany economy (e.g., Hubrich and Vlaar 2004), we control for a potential break in the GDP-per-capita and the private-label-share series in 1990 when we derive fluctuations that can be attributed to the business cycle (for more details, see Appendix A). The parameters associated with the pulse dummy in Equation A3 were insignificant and do not affect the cyclical components derived from the West German private-label-share and GDP-per-capita series, respectively. Thus, the German reunification does not alter any of our prior findings.

Discussion

In this study, we examined the sensitivity of private-label share to the aggregate business cycle for several key private-label countries. In the beginning of the article, we identified three research questions that this study attempted to address. We summarize our findings in relation to these questions. First, we find that private-label success indeed behaves countercyclically. Several academics and practitioners have theorized that there is an inverse relationship between the state of the economy and private-label performance, but with the exception of Hoch and Banerji (1993), our study is the first to test this hypothesis rigorously. Our analysis confirms this conventional wisdom from a business-cycle perspective; that is, a country's private-label share increases when the economy is suffering and shrinks when the economy is flourishing.

Second, private-label performance behaves differently over expansion and contraction periods. This is a new finding that has not been examined in previous research. We find that business-cycle fluctuations induce asymmetries in both the extent and the speed of up- versus downward movements in private-label share.

Third, the aggregate business cycle contributes to long-term private-label success. Not only does the sequence of contractions and expansions induce temporary upward and downward swings in private-label share, but we also find that part of the share gain during contractions is permanent. This is also an important new finding, which contradicts a long-held opinion that private labels "are discarded once the economy picks up again" (Ward et al. 2002, p. 962). Thus, not only are consumers more prone to buy private labels during economic downturns, but some of them also keep buying these store-brand alternatives when bad economic times are long over.

Managerial Implications

Economic recessions contribute to the prolonged upward evolution in private-label share, leaving permanent scars on national brands' performance levels. Business-cycle fluctuations are beyond the control of individual brand managers. However, managers might mitigate the effect of an economic downturn on their brands' positions by engaging in proactive marketing, a strategy in which the firm views the recession as an opportunity and invests aggressively in marketing activities during downturns. This strategy has been found to result in improved performance not only during contractions but also in subsequent expansion periods (Hillier and Baxter 2001; Srinivasan, Rangaswamy, and Lilien 2005).

Unfortunately, however, the behavior of most brand managers appears to be anything but proactive. Indeed, their behavior might actually exacerbate the negative effects of an economic downturn on their brands' positions. The key driver behind this is managers' short-term focus. After all, most managers spend no longer than three years in the same job (Kerin 2005) and thus may be prone to underweigh long-term implications of their short-term decisions. In this context, Milgrom and Roberts (1992, p. 471) observe that a manager "will be tempted to put too much emphasis on activities that boost short-term performance compared to those whose benefits will be hidden ... for a long period of time."

To protect short-term profits, managers want fast ways to cut costs in times of slow demand. Two common ways to achieve this are scaling back of innovation activity (Axarloglou 2003) and cutting advertising budgets (Picard 2001). Table 5 offers additional evidence on advertising retrenchment during a recession for ten major national CPG brands in the United Kingdom. Expenditure on these activities is often discretionary, and cutting them directly affects the bottom line, though their adverse effects may be revealed only in the longer run.

The apparently widespread practice of reducing brand support during bad economic times could reinforce the impact of the business cycle in favor of store-brand alternatives. However, is it true that innovation and advertising can reduce the negative effect of an economic downturn for brand manufacturers? If these instruments are not effective, managers' behaviors might be perfectly rational. Although there is little hard evidence, there is indirect support that innovation and advertising can indeed serve this role for manufacturer brands. Several authors have speculated that private labels are less successful in categories characterized by intense innovation activity (Quelch and Harding 1996;

TABLE 5
Average Yearly Growth in Advertising Expenditures for Several Top Brands in the United Kingdom

	Expansion Period (1997–1998)[a, b]	Contraction Period (2001–2002)[c]
Aquafresh	+.03	–.25
Colgate	+.11	–.18
Danone	+2.80	–.01
Guinness	+.04	–.15
Heinz	+.68	–.25
Kellogg's	+.03	–.34
Kraft	+.24	–.30
Nescafé	+.21	–.51
Nestlé	+.87	–.16
Persil	+.11	–.11

[a] We determined contraction and expansion years on the basis of the HP-filtered GDP-per-capita data of the United Kingdom.
[b] Average yearly growth between 1997 and 1998.
[c] Average yearly growth between 2001 and 2002.
Notes. We obtained advertising-expenditure data from ACNielsen Media Research U.K.

Steenkamp and Dekimpe 1997). Moreover, Hillier and Baxter (2001) show that firms that increase their product development spending during a recession perform better in terms of profitability and market share during the subsequent recovery. Although this does not prove that innovation is effective as a barrier against private-label success in recessions, at the very least, it suggests that reducing innovation activity in economic downturns is not conducive to fight private labels.

Because most CPG categories are mature, the positive role of advertising may appear less obvious. However, advertising is crucial to maintain product differentiation with private labels, which is necessary to justify the price difference (Hoch and Banerji 1993). Frankenberger and Graham (2003) report that firms that increased their advertising expenditure in a recessionary period created added value that extended through the year following a recession. However, the company is advised not to rely on advertising in isolation but rather to use it in combination with the introduction of new products. Lodish and colleagues (1995) report that the advertising elasticity for new products is five times higher than it is for established products. Similarly, Steenkamp and Gielens (2003) find that new products that were heavily advertised achieved a trial rate that was 72% higher than the trial rate of new products that did not receive much advertising support.

Taken together, these findings imply that proactive marketing involving new-product introductions supported by heavy advertising may be a powerful strategy to mitigate the effect of a recession on the position of manufacturer brands. Proactive marketing in times of recession may offer the key for national-brand manufacturers to prevent consumers from (permanently) switching to private-label offerings. One company that has successfully followed this route is U.K.-based Reckitt Benckiser.[12] Despite difficult economic times in many of its markets, it has managed real top-line growth (and doubled profitability) through hefty product innovation—40% of sales are from products launched in the last three years—and by investing much more heavily in advertising than most of its competitors. Notably, another "discretionary" marketing activity, marketing research, plays a key role in this process. Product development is based on ideas generated by marketing research and are tested with consumers before launch (*Financial Times* 2005).

Contrary to most manufacturers, anecdotal evidence suggests that retailers actually exploit the benefits of proactive marketing because they tend to increase their private-label support in recessions. For example, the British supermarket chain J. Sainsbury responded to difficult trading times in the beginning of the 1990s by increasing its promotional emphasis on own-label products with price reductions on some 300 of these items (Walters 1994). As another illustration, more than one-third of all new-product launches in Germany during the economically depressed period of 2001–2003 were private-label brands (Kumar and Steenkamp 2006). Through such countercyclical private-label support activities, retailers may significantly contribute to long-term private-label performance. Thus, although the impact of the aggregate business cycle may seem uncontrollable, a proactive marketing strategy by manufacturers and retailers may either mitigate or accentuate the observed dependency of private-label success on general economic conditions.

Limitations and Directions for Further Research

Our study has several limitations that offer interesting avenues for further research. Future studies should examine the interplay between consumer actions and manufacturer or retailer behavior to assess the relative contribution to the increased popularity of private labels during contractions. If this phenomenon is driven mainly by consumer behavior in response to changes in the economic climate, this does not bode well for national-brand manufacturers, because part of private-label success is beyond their control.

Conversely, if manufacturer behavior is an important factor in explaining private-label success over the business cycle, what can managers do to reverse this? Can increased new-product development mitigate the effect of a recession for manufacturers? Can advertising staunch the loss of market share in an economic downturn, and if so, what advertising medium and content are most effective in recessionary times? Is it better to spend the money on price promotions, despite their often modest pass-throughs? Which marketing instrument is most effective and cost efficient? Can synergies be obtained by using several instruments simultaneously? Finally, why does available evidence, admittedly anecdotal, indicate that managers apparently behave in ways that hurt the long-term prospects of the company? Do they not know this, or do they unreasonably discount future profits? How can performance evaluation criteria and career paths be adapted to prevent unreasonable discounting?

On the part of the retailer, it is fruitful to consider whether actions during recessionary periods really reinforce the cyclical sensitivity of private labels and what kind of actions are most successful to strengthen the boost in private-label sales. Retailers should also give closer consideration to the profitability of private labels. Even if their behaviors increase private-label success in recessions, are they better off financially after the relevant criterion—annual dollar contribution per square foot of shelf space—is considered? From a more technical point of view, further research could develop an integrated (potentially nonlinear) model that enables the investigation of the four components of the business cycle in a single step rather than our current multistep procedure.

In summary, our study formally examines how the popularity of private-label alternatives is related to aggregate business-cycle fluctuations in a CPG setting and offers evidence on the much-debated and speculative idea that private labels are only for recessionary times. We propose a framework that helps understand and predict the observed net effect on private-label performance. However, more research is called for to identify which part of the observed negative effect of a recession on national-brand sales can be offset by manufacturers and which factors underlie the observed patterns. We hope that our article provides an impetus to this much-needed research effort.

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[12] Examples of Reckitt Benckiser brands in the United States are Lysol, Woolite, Calgon, Veet, Air Wick, Electrosol, and Spray 'n Wash.

Appendix A

The HP filter can be rationalized as the optimal estimator of the trend in the following structural model (Harvey and Jaeger 1993):

$$y_t = y_t^l + y_t^c, \quad y_t^c \sim N(0, \sigma_{y^c}^2), \tag{A1}$$

where the trend component y_t^l is modeled in general state-space form as

$$\begin{aligned} y_t^l &= y_{t-1}^l + \beta_{t-1} + \eta_t, & \eta_t &\sim N(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \varepsilon_t, & \varepsilon_t &\sim N(0, \sigma_\varepsilon^2), \end{aligned} \tag{A2}$$

where $\sigma_\varepsilon^2/\sigma_{y^c}^2 = 1/\lambda$, where λ is the smoothing parameter or penalty that determines the degree of smoothing. In line with the work of Boone and Hall (1999), we normalize $\sigma_{y^c}^2$ equal to 1. By imposing a value for λ equal to the smoothing parameter in Equation 1 and setting σ_η^2 equal to 0 in Equation A2, this general structural time-series model produces a trend and a cyclical component that are identical to those obtained using the well-known HP filter. The conversion of the HP filter into Equation A2 and A3 enables us to adopt the Kalman filter to calculate maximum likelihood estimates of the trend component.

To control for a potential break in the series after a certain point in time (τ), we can extend the HP filter formulated in Equations A1 and A2 with two pulse dummies that can account for a potential change in the level and the trend of the series. The resulting state-space form of the trend, y_t^l, in Equation A2 then becomes

$$\begin{aligned} y_t^l &= y_{t-1}^l + \beta_{t-1} + \gamma_1 D_\tau, \\ \beta_t &= \beta_{t-1} + \gamma_2 D_\tau + \varepsilon_t, \ \varepsilon_t \sim N\left(0, \frac{1}{\lambda}\right), \end{aligned} \tag{A3}$$

$$\text{where } D_\tau \begin{cases} = 0 & \text{if } t \neq \tau \\ = 1 & \text{if } t = \tau. \end{cases}$$

For a similar extension of the business-cycle filter with break dummies, see Boone and Hall (1999).

Thus, when we filter out the fluctuations due to the business cycle, the state-space formulation (Equation A3) enables us to control for a potential break in a series (e.g., the German reunification in 1990).

Appendix B

We express the quantities $\hat{\zeta}_1$, $\hat{\zeta}_2$, and $\hat{\zeta}_3$ in terms of probabilities and computed them as

$$\hat{\zeta}_1 = \frac{1}{T}\sum_{i=1}^{T}[\hat{f}_1^*(X_i) - \hat{\eta}]^2, \tag{B1}$$

$$\text{where } \hat{f}_1^*(X_i) = \frac{1}{\binom{T-1}{2}} \sum_{\substack{j<k \\ i \neq j \neq k}} \sum f^*(X_i, X_j, X_k), \text{ and}$$

$$f^*(X_i, X_j, X_k) = \frac{1}{3}\begin{bmatrix} \text{sign}(X_i + X_j - 2X_k) \\ + \text{sign}(X_i + X_k - 2X_j) \\ + \text{sign}(X_j + X_k - 2X_i) \end{bmatrix};$$

$$\hat{\zeta}_2 = \frac{1}{\binom{T}{2}} \sum_{j<k} \sum (\hat{f}_2^*(X_j, X_k) - \hat{\eta})^2, \tag{B2}$$

$$\text{where } \hat{f}_2^*(X_j, X_k) = \frac{1}{T-2} \sum_{\substack{i=1 \\ i \neq j \neq k \\ i \neq k}} f^*(X_i, X_j, X_k); \text{ and}$$

$$\hat{\zeta}_3 = \frac{1}{9} - \hat{\eta}^2. \tag{B3}$$

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Gary K. Hunter & William D. Perreault Jr.

Making Sales Technology Effective

Firms invest billions of dollars in sales technologies (STs; e.g., customer relationship management, sales automation tools) to improve sales force effectiveness and efficiency. However, the results expected from ST investments are often not achieved. This article proposes relationship-forging tasks that are critical to the link between ST use and key aspects of salesperson performance (i.e., a salesperson's relationship-building performance with customers and administrative performance). The authors evaluate relationship-forging tasks in the context of a model that considers the antecedents and consequences of three different uses of ST: accessing, analyzing, and communicating information. In general, the results of a field study, which is analyzed using block-recursive structural equation modeling, support the relationship-forging theory and show that relationship-forging tasks predict 57% of the variance in a salesperson's relationship-building performance with customers. The findings also support hypotheses that using ST either to analyze or to communicate information has mediated positive effects on a salesperson's relationship-building performance with customers. However, a salesperson's use of ST to analyze information has negative influences on administrative performance, creating an unexpected trade-off for sales and marketing managers.

The nature of exchange processes between buyers and sellers in business markets has changed dramatically. Cooperative partnerships rather than competitive actions (Anderson and Narus 1984, 1990), a search for integrative rather than distributive (win–lose) outcomes (Clopton 1984), and long-term rather than short-term outlooks (Dwyer, Schurr, and Oh 1987; Ganesan 1994) better characterize buyer–seller relationships than does the traditional "arm's-length exchange" process. Over the past decade, sellers have placed increased strategic emphasis on building relationships with buyers (Cannon and Perreault 1999) and investing in information technology (IT) for sales force applications (Shoemaker 2001). However, many sales forces have preserved their primary responsibility of establishing, building, and maintaining relationships with business customers. Considering the current state of buyer–seller relationships, it is not surprising that in a recent worldwide study of 1300 companies, executives ranked sales force effectiveness second only to revenue generation as their top priority (Dickie 2004). Thus, the strategic importance of the sales force to the organization's success may be at an all-time high.

Concurrent with renewed strategic importance, sales organizations seek new ways to use IT. In today's relational selling role, the sales representative's job is no longer to protect the host organization from external dependencies and advance solely its internal objectives; rather, the purpose is often just the opposite. The salesperson's new imperative is to help forge relationships and heighten cooperation with customer firms. To do this, sales representatives must identify, create, develop, and propose ways to integrate the objectives of both buyers and sellers while reducing their differences. This places new demands on the salesperson's skills and abilities to create integrative buyer–seller solutions, convert increasing amounts of data into useful market knowledge, and discover innovative ways to use IT tools.

Although the new relational selling era often demands consultative selling processes, these processes are coupled with massive and often problematic investments in IT (Speier and Venkatesh 2002). Considering the high costs of sales technology (ST) implementations and their associated failure rates, it is not surprising that ST is a high priority in sales management research (Leigh and Marshall 2001).

Advances in IT have reshaped all aspects of marketing, but impacts on buyer–seller relationships in business markets are especially dramatic. At one extreme, some customer firms use Internet procurement hubs and reverse auctions to increase competition among sellers and help drive down procurement costs (Jap 2003). In other markets, sellers and their customers rely on technology to share information seamlessly and support operational linkages that are part of a close, cooperative, and continuing relationship (Cannon and Perreault 1999). From a seller's perspective, the former approach stresses competition on costs, and the latter presents an opportunity for revenue expansion strategy (e.g., investing in customer service, customer satisfaction, and customer retention). Specifically, firms can invest in their sales force to build better relationships with buying firms.

Recent research has shown that firms realize better financial returns by pursuing revenue expansion strategies (Rust, Moorman, and Dickson 2002). However, to implement such strategies within a sales organization, managers need a better understanding of how salespeople can use IT to perform selling tasks that improve the sales representative's relationship-building performance with customers.

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The purpose of this research is to develop and test a theoretical model that explains the mechanisms by which the uses of ST simultaneously influence relationship-building and administrative performance. Here, we propose that beyond the commonly sought returns on administrative performance offered through ST, salespeople can use IT to perform key tasks that help them build better business relationships with customers. A necessary condition for achieving mutually beneficial returns from a sales organization's perspective is sales representatives' performance on tasks that help integrate the buyer's and the seller's objectives.

Not surprisingly, sales organizations have an expanding interest in developing new relational selling processes to implement revenue expansion strategies, and these interests help catalyze ST industries. To clarify and frame this research, we briefly address several relevant terms—including customer relationship management (CRM), sales (force) automation (SFA), and ST. Then, we propose a formal model that describes how different uses of ST affect key aspects of sales performance in a relational context.

CRM, SFA, and ST

Customer relationship management has been so pervasive that it has evolved both as a business philosophy and as a technology (Johnston and Marshall 2006). As a business philosophy, Srivastava, Shervani, and Fahey (1999, p. 169) view CRM as one of three core macrolevel business processes and define it as "all aspects of identifying customers, creating customer knowledge, building customer relationships, and shaping their perspectives of the organization and its products." Others use the term CRM to refer to "the use of technology to manage customer interactions and transactions" (Zoltners, Sinha, and Zoltners 2001, p. 389), which explicitly recognizes technology's importance to CRM processes. Vendors of CRM technology have become a multibillion dollar industry. However, technologies alone often cannot perform the CRM business process that Srivastava, Shervani, and Fahey describe. Such a process often requires skills that only people have and that technology cannot replace. Yet those people often use technological tools to implement the CRM business process.

Sales-based CRM technology tools are specifically designed to help the sales organization meet its objectives in managing customer relationships. In addition, many SFA vendors offer tools that are intended to make repetitive (administrative) tasks more efficient. These vendors stress that sales representatives who complete routine tasks faster, easier, or better become more productive overall by reallocating time gains to more "face time" with buyers. For example, contact management software helps sales representatives manage leads, track all communications with customers, schedule follow-ups, or handle time management and planning tasks. In contrast to much of the extant literature, salespeople use an even broader range of technologies for managing relationships than those offered by sales-based CRM or SFA vendors, including general purpose hardware and software tools. For example, salespeople use cell phones for communications and spreadsheets for analysis, two technology tools that many sales managers consider critical to managing relationships with customers, yet few experts classify cell phones or spreadsheets as CRM or SFA technologies. In this article, ST represents the broad range of ITs that salespeople use; thus, we consider sales-based CRM a subset of ST tools.

Specifically, ST refers to ITs that can facilitate or enable the performance of sales tasks. Thus, ST tools include spreadsheets, relational database programs, Nielsen/Information Resources Inc. scanner data analytical programs, sales forecasting tools, inventory management systems, contact management programs, multimedia hardware, cell phones, graphics software, image projectors, computer-based presentations, e-mail, Web browsers, and so forth. Essentially, we view ST tools as spanning the entire gamut of ITs that salespeople use to perform their roles, not just the subset designed as sales CRM or SFA tools.

From Motivating ST Use to Sales Performance

Although vendor obsession with increasing ST use may represent sound marketing strategy, there has been a pervasive scholarly focus on motivating user acceptance (Venkatesh and Davis 2000). A common underlying assumption in both practice and academic research is that motivating use is *the* critical issue and panacea for implementation success from user acceptance of ST. Even if the positive returns exist in marketing and sales contexts, more theorizing and research is needed to further the understanding of the antecedents and consequences of technology uses. Importantly, there are different ways to use technology tools.

This research builds on the current literature, but it also represents a fundamental departure by arguing that implementation success requires more than user adoption or the supply of an ideal portfolio of ST tools. We argue that implementations benefit from an understanding of how different uses of technology influence the sales behaviors that drive sales performance. We propose a new way of thinking about different dimensions of use for accessing, analyzing, and communicating information. In essence, we argue that user acceptance of technology may be a necessary, but not a sufficient, condition for implementation success.

To provide a better understanding of ST success, we develop a model of how different uses of ST affect relationship-building behaviors, which drive key aspects of performance. This effort builds on recent research that has proposed and tested a "selling smart with technology" model and has found that an overall measure of ST use affects sales performance through adaptive selling and sales planning behaviors (Hunter, Perreault, and Armstrong 1998). In contrast, although salespeople and sales managers may hold idiosyncratic mental models that cognitively represent how sales behaviors influence sales performance (e.g., beyond adoption), mental models are useful only if they are accurate (Johnson-Liard 1983, p. 4). The empirical testing we use is one means for assessing the accuracy of such mental models.

Given the strategic importance of ST, managers can no longer be satisfied with motivating technology adoption, relying on untested mental models, or even knowing that they have supplied representatives with the most promising ST tools. Although models of behaviors precede estimates on economic returns, managers need to advance and test models that link a salesperson's uses of technologies to his or her conduct of desirable tasks.

The current literature provides limited theorizing or empirical evidence on how different types or ST uses affect measures of sales performance (e.g., Hunter, Perreault, and Armstrong 1998), especially with respect to a representative's efforts to forge stronger relationships with customers. We do not suggest that there has not been attention to different types of ST (e.g., Wedell and Hempeck 1987) or to approaches for evaluating aggregate-level ST successes and failures (e.g., Speier and Venkatesh 2002). Although achieving increased administrative performance is an important objective, ST can also enable sales representatives to perform new tasks that result in better and more profitable relationships with and for customers. In addition, although one-dimensional conceptualizations of use provide enlightening theoretical and empirical results, a consideration of multiple dimensions of use may enrich the understanding of ST as well. In essence, there is a gap in the literature regarding how different uses of ST influence behaviors that can help representatives build stronger relationships with customers and improve administrative performance.

This research addresses this important knowledge gap by building on and integrating theories that originate from six literature streams: relationship marketing, buyer–seller relationships, organizational learning, cognitive selling, negotiations, and IT productivity. It contributes to this thinking by developing and testing the measures and mechanisms of a behavioral process model that shows how salespeople simultaneously complete a set of relationship-forging tasks, and it estimates effects on relationship-building and administrative performance. We conceptualize three basic uses of ST for accessing, analyzing, and communicating information, and we clarify the roles of each type in the relationship-building process. To obtain a more comprehensive understanding of the effects on sales performance, we control for sales experience and effort.

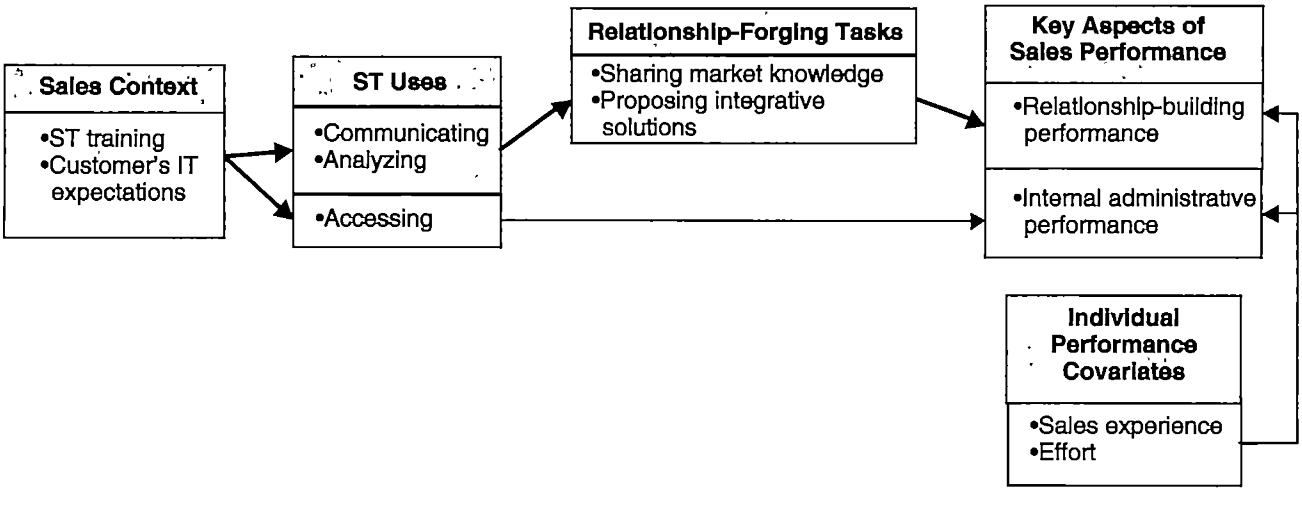
In the next section, we propose a parsimonious theoretical model. Then, we report the results of a field test of the model based on structural equation modeling (SEM) methods. Our results support this theorizing and highlight a trade-off in technology uses that we did not expect. Our conceptual and empirical contributions lead to a discussion of the managerial and research implications of this work.

Theoretical Model Development

Relationship-forging tasks are activities that an individual in an organization performs to help build relationships with external constituents. In sales organizations, representatives conduct these tasks to build better relationships with business customers.

The theoretical model that we summarize in Figure 1 takes these ideas further and develops them in the context of a more complete set of hypothesized relationships. It is useful to think of the constructs and paths shown in Figure 1 as a process model for evaluating the impact of different uses of ST on sales performance. Specifically, the model proposes that uses of ST influence relationship-building performance with customers indirectly through a mediated relationship-forging process. This behavioral process modeling approach integrates literature for evaluating the impact of IT and builds on the rich tradition of previous studies on boundary spanning and salesperson performance (see, e.g., Anderson and Robertson 1995; Behrman and Perreault 1984; Cravens et al. 1993; Oliver and Anderson 1994; Singh 1998; Sujan, Weitz, and Kumar 1994). This research recommends diagnosing ST implementation issues by first identifying the desired aspects of sales performance and then working backward to conceptualize the tasks that constitute the sales process, ST uses, and the antecedents that influence them.

FIGURE 1
Conceptual Model of Antecedents and Outcomes of Different Types of ST Use and Relationship-Forging Tasks


Sales Context
•ST training
•Customer's IT expectations
ST Uses
•Communicating
•Analyzing
•Accessing
Relationship-Forging Tasks
•Sharing market knowledge
•Proposing integrative solutions
Key Aspects of Sales Performance
•Relationship-building performance
•Internal administrative performance
Individual Performance Covariates
•Sales experience
•Effort

Key Dimensions of Sales Performance

Sales performance is defined as "*behavior* evaluated in terms of its contribution to the goals of the organization" (Johnston and Marshall 2006, p. 412, emphasis added). This definition is consistent with previous research on sales performance (Anderson and Robertson 1995; Behrman and Perreault 1982, 1984; Cravens et al. 1993; Oliver and Anderson 1994; Singh 1998; Sujan, Weitz, and Kumar 1994). Here, we focus on literature that is most relevant to this study, but Brown and Peterson (1993) provide a thorough meta-analysis of studies in the area of salesperson performance.

According to boundary role theory, salespeople represent the physical manifestation of the firm's boundaries and are the "linking pins" between buyers and sellers (Adams 1976). Although boundary role theory was conceived before the modern era of CRM, it is still useful in delineating a duality in roles for salespeople. Inherently, some sales tasks focus more internally on the sales organization, whereas others center more externally on market constituents.

With respect to more externally focused behaviors, though a quantitative outcome-based measure of sales performance (e.g., sales unit, dollar volume) may be an important aspect (or objective) of salesperson behavioral performance (Anderson and Oliver 1987), it can also be precisely the wrong measure in a relational selling context. As IBM found in the early 1990s, sales representatives produced high-volume sales when they pushed mainframes, but many customers were alienated when they realized that they had been sold the wrong product. This is one reason IBM moved to incorporate relational measures of sales performance that stress behaviors over outcomes. In addition, research has shown that sales territory characteristics and potential, not salesperson skill and effort, explain most of the variance in external measures of sales volume (Zoltners, Sinha, and Zoltners 2001). As an alternative to outcome-based measures of sales performance, a prominent stream of research on sales performance has shown that sales organizations may benefit from the use of behavior-based sales control systems (e.g., Anderson and Oliver 1987; Cravens et al. 1993). Collectively, these studies suggest examining a salesperson's behaviors toward building relationships with customers as a key aspect of externally oriented sales performance.

Specifically, relationship-building performance with customers is the extent to which the salesperson performs activities that cultivate a relationship that mutually benefits the selling and buying firms. A mutually beneficial relationship is not one that yields returns only to the sales firm. At the same time, we do not imply that the salesperson should abandon the needs of the seller. Finally, the distribution of outcomes does not necessarily result in an "even split." Examples of this approach include "building your customer's business with your products" and "working with buyers to develop a partnership that's profitable to both firms."

In contrast, a dominant internal concern for sales performance includes the salesperson's conduct regarding administrative behaviors. Administrative performance refers to the salesperson's ability to complete his or her required, nonselling-related activities in a timely manner (this often involves an internal focus). "Submitting required reports on time" is a behavior that represents this construct.

A widely accepted logic is that SFA tools yield increased administrative performance, and this frees up incremental personal selling time for customer contact and other relationship-building activities. Thus, we expect that there is covariance among these sales performance constructs.

Although it is desirable to advance and test a parsimonious explanation of the performance impact of different uses of ST, there is a trade-off with complete specification of other potentially relevant performance predictors. Therefore, the model explicitly recognizes individual differences in salesperson effort and experience as important (exogenous) drivers of sales performance (Brown and Peterson 1994).

Relationship-Forging Tasks

Research in relationship marketing stresses the important role of trust and commitment to interorganizational relationships (Atuahene-Gima and Li 2002; Doney and Cannon 1997; Dwyer, Schurr, and Oh 1987; Ganesan 1994). However, more research is needed on other factors that influence a salesperson's performance in a relational context.

March and Simon (1958) were early proponents of the use of interorganizational relationships as an important means for advancing organizational learning. In addition to inspiring research on trust and commitment, social exchange theory stresses information exchange (Thibaut and Kelley 1959) and the importance of bargaining and negotiating on buyer–seller relationships (Clopton 1984).

Regarding information exchange, Day's (1994) market-sensing model proposes that sharing information is an important part in the relationship-building process. Likewise, analytical and simulation researchers have devoted much attention to the role of information sharing in interorganizational relationships (e.g., Li 2002; Raghunathan 2001).

Negotiations have a long-standing history in personal selling. Strategically, sales organizations confront two fundamental alternatives between coordinative and competitive negotiation strategies across customer accounts. Competitive strategies have their basis in fixed outcomes, whereas a coordinative negotiation strategy calculates mutually beneficial returns (Pruitt 1981), including pie expansion (Jap 1999). Clopton (1984) highlights the potential benefits offered to business market salespeople who use integrative as opposed to distributive outcomes in buyer–seller relationships. Subsequent field studies have supported this general notion (e.g., Jap 1999). In addition, in a business-to-business (B2B) services selling environment, the buyer's perceptions of the salesperson's cooperative (versus competitive) negotiation strategies have been linked to buyer–seller relationship quality (Crosby, Evans, and Cowles 1990).

Clopton (1984) also notes that when presented with ambiguous information, buyers and sellers in a negotiation may not be aware of a means to arrive at an integrated, win–win outcome. For example, a salesperson might promise a customer firm a higher-quality standard on component parts, but the customer may not recognize the seller's costs or complications in meeting that promise and thus may undervalue the concession. A less costly concession, such as providing more reliable order-cycle times, could have more impact on the customer's profits. The ambiguous nature of information does not need to be based on the salesperson's decision to withhold the information but rather on the salesperson's potential inability to distill market knowledge. Thus, Clopton's study suggests that sharing knowledge and pursuing integrative negotiation strategies are important to B2B relationships.

Building on this literature, as Figure 1 shows, we specify and develop measures for two key relationship-forging tasks: sharing market knowledge and proposing integrative solutions to customer problems. Links in the model reflect the hypotheses that sharing marketing knowledge and proposing integrative solutions improves the salesperson's relationship-building performance with customers. However, in Figure 1, there is no direct hypothesized link between the relationship-forging tasks and administrative performance.

Sujan, Sujan, and Bettman (1988) find that higher-performing salespeople do not necessarily have more knowledge categories, but rather better qualitative distinctions among categories. Similarly, Szymanski (1988) shows that declarative knowledge (how categories are organized in memory) and the accurate identification and classification of the categories distinguish effective salespeople from ineffective salespeople. Collectively, studies employing the cognitive sales paradigm show why an expert salesperson outperforms a novice at different stages of the selling process (see Macintosh et al. 1992).

Sharing market knowledge refers to the extent to which salespeople develop relevant market expertise and share their knowledge with their customers. Developing expertise that makes a sales representative a knowledgeable resource, even to his or her peers within the sales organization, provides the necessary foundation on which customer accounts may benefit. Converting data into knowledgeable insights that can be shared with customers helps distinguish the quality of the service provided by a sales representative from the sales services provided by the firm's competitors. Representatives with high levels of market expertise have a decisive advantage over their more novice competitors in sharing market knowledge with customers.

> H_1: Salespeople who share market knowledge with customers are conducting an activity that forges relationships between the buying and the selling firms.

Proposing integrative solutions refers to the extent to which salespeople apply information and knowledge to construct and propose recommendations that are mutually beneficial to both the selling and the buying firms. Constructing such recommendations requires the salesperson to develop solutions that integrate the objectives of the selling firm into solutions that also work for the buying firm. For example, a sales representative combines knowledge of his or her own firm's capacities and costs with analysis of the customer's inventory costs to forecast alternative courses of actions. The representative may then propose mutually beneficial courses of action that help forge relationships between the firms.

> H_2: Salespeople who propose integrative solutions to customers are conducting an activity that helps forge relationships between the buying and the selling firms.

It also makes sense that salespeople who share market knowledge with customers might also propose integrative solutions to them. Therefore, we expect covariance between the relationship-forging constructs.

Uses of ST and Their Impacts

Just as there are different ways to measure performance, researchers have examined IT from different perspectives. An approach that is popular in the IT literature is to model the return on total investment in IT (e.g., Bharadwaj, Bharadwaj, and Konsynski 1999). Although "black-box" approaches offer important strategic insights, they have routinely produced conflicting results, and these models are silent on the behavioral process through which technology influences sales performance (for a discussion, see Hitt and Brynjolfsson 1996).

During the early evolution of ST, marketing scholars (e.g., Collins 1989; Collins and Schibrowsky 1990) focused on normative prescriptions about potential uses of individual software and hardware innovations (spreadsheets, contact management software, and several others). Similarly, many companies rely on user evaluations and acceptance of individual STs, an approach recommended in the IT literature (Venkatesh and Davis 2000). This can be useful, but user evaluations of individual technology tools alone can result in misleading conclusions. The behavioral explanation is simple: Salespeople who do not rely on or use a particular technology report that it is not useful to them, but if they use the technology (e.g., because of better training), such use might improve their performance. This is the underlying logic for benchmarking behaviors or identifying best practices.

In contrast, the task–technology fit theory approach relies on user judgments (ratings) to evaluate individual technology tools or IT systems (see Goodhue 1995a, b, 1998). Although there are benefits to this approach, including ease of implementation, our approach relies on empirical evidence of technology effects rather than user judgments. Specifically, the salesperson (user) provides information about his or her performance of sales tasks and technology use. Then, we empirically estimate the effect of technology uses on sales behaviors and aspects of sales performance. This helps camouflage our hypotheses and thus reduces demand characteristics (cues) that increase the likelihood of bias in responses (Shimp, Hyatt, and Snyder 1991). Thus, if we simply provided representatives with our hypothesized model and asked them to rate the effects, we would increase the likelihood of demand artifacts that challenge the study's validity.

A concern with measuring technology use involves deciding on suitable aggregation. Building on Huber's (1991) work, Sinkula (1994) argues that consideration of multiple dimensions of information use is important in understanding how firms (or individuals) process market information. Thus, our conceptualization of different dimensions for uses of ST adopts both Huber's and Sinkula's thinking.

Huber's (1991, p. 90) work on organizational learning defines four organizational learning processes. Knowledge acquisition is "the process by which knowledge is obtained." Information interpretation is "the process by which distributed information is given one or more commonly understood interpretations." Information distribution is "the process by which information from different sources is shared and thereby leads to new information or learning." Organizational memory is "*the means* by which knowledge is stored for future use" (emphasis added).

In this study, "accessing" information represents learning through knowledge acquisition, "analyzing and better understanding" information parallels Huber's (1991) information interpretation, and "communicating" represents Huber's information distribution. Except for organizational memory, Huber's conceptualizations define learning processes as opposed to learning means. Thus, our model does not explicitly incorporate organizational memory. However, this adaptation reflects a difference in the IT and salesperson (user) view that we want to advance; this was motivated, in part, on the basis of feedback from sales managers during qualitative interviews about uses of ST. They noted that though IT specialists often focus on the storage capacity of hardware and software, from a user's perspective, the issue is whether information can be accessed. A mass of data that is stored in organizational memory but is not accessible has no measurable influence on salesperson behavior. The salesperson may fill a role in inputting information into organizational memory, but it is the salesperson's next (temporally lagged) use of technology to access that information (and other sources) that we measure and model here.

Formally stated, "using ST for accessing information" refers to the extent to which salespeople use technology to obtain information relevant to performing their sales jobs. The sales representative might use different technologies to access information about products, sales calls, orders, sales, accounts, and the like. Sales representatives may vary with the frequency, emphasis, and confidence with which they use these tools. Similarly, "using ST for analyzing information" refers to the extent to which salespeople rely on IT to study or synthesize data and understand the implications of patterns of data relevant to the demands of their sales jobs. Finally, "using ST for communicating information" refers to the extent to which salespeople use technology to disseminate information and knowledge to others in performing their jobs. As these conceptualizations suggest, our focus is on different dimensions for uses of ST rather than on an individual application by itself.

The distinction between using ST for accessing information and using ST for analyzing or communicating information warrants elaboration. To analyze information, it must be accessible, and the content or value of communication improves when it is based on good information (perhaps supplemented by analysis). The sales representative's administrative performance improves if there is ready access to relevant information. Easy access reduces both search time and confusion that might arise from information gaps associated with information that is too difficult, time consuming, or costly to obtain. Conversely, analyzing and communicating are aspects of IT use that leverage available information and turn it into usable knowledge. However, we do not advance directional hypotheses for the relationships between the different uses of technology, because it is likely that the relationships are interactive and that there are potential feedback loops across the three categories of technology use.

> H_3: Use of ST for communicating information increases the practice of sharing market knowledge.

Recent research on team dynamics has found that perceived experts are more likely than their novice counterparts to share knowledge (Thomas-Hunt, Ogden, and Neale 2003). In the context of buyer–seller relationships, expertise can provide a source of power and influence (French and Raven 1959) that encourages the salesperson to share that expertise with the buying firm. Using IT to analyze information helps salespeople gain declarative knowledge. The greater the salesperson's declarative knowledge, the more open he or she will be to sharing it.

> H_4: Use of ST for analyzing information increases the practice of sharing market knowledge.

It is typically more difficult for a sales representative to identify integrative solutions than it is to develop distributive ones. As we detailed previously, identifying integrative solutions requires the understanding and alignment of objectives across firms, whereas a distributive approach requires only a focus on the seller's objectives. Sales technologies can help salespeople sort, summarize, or break down complex data that are relevant to calculating the costs and benefits of various recommendations from the perspective of the selling firm, the buying firm, and the end consumer. For example, a salesperson could take advantage of a user-friendly interface to a large database to access information about product markets. Indeed, demand for tools that ease access to information has led some leading vendors, including IBM, to develop portals for gathering market intelligence. However, simply accessing information usually does not lead to an integrative proposal. Often, information does not become usable knowledge without further value-adding activity. For example, a salesperson could use statistical analysis software to estimate outcomes of alternative proposals and prepare graphics to help communicate a recommendation.

The relationship marketing literature stresses the need for communications in building better buyer–seller relationships (Mohr, Fisher, and Nevin 1995; Mohr and Nevin 1990). In addition, the expanding literature on modeling scanner data shows the need for analysis in building better channel relationships (Raju and Roy 2000). Conversely, this implies that using technology to access information does not have a direct impact on relationship-forging tasks except to the extent that accessing information simplifies (or covaries with) use of technology for analyzing and communicating.

KP 2671

H_5: Use of ST for (a) analyzing and (b) communicating information increases the practice of proposing integrative solutions

As previous work on the role of SFA highlights, use of IT should improve administrative performance (Hunter, Perreault, and Armstrong 1998). Although previous studies examine the aggregate effects of general technology use on administrative performance, we propose that administrative performance gains will be realized across all three dimensions of use (accessing, analyzing, and communicating information) examined here. As an example, using technology to access information should improve a salesperson's ability to be timely in completing administrative responsibilities. Thus:

H_6: Use of ST for (a) accessing, (b) analyzing, and (c) communicating information improves internal administrative performance.

Facilitating Conditions That Affect ST Uses

Jones, Sundaram, and Chin (2002) highlight the need for salespeople to adopt ST when forming customer alliances and find that personal innovativeness, attitude toward the new ST, and facilitating conditions influence ST infusion. Although our primary focus is on relationship-forging tasks, technology uses, and different aspects of performance, we consider two facilitating conditions pertaining to, or social system influences on (e.g., Fulk 1993), the uses of ST. "Sales technology training effectiveness" refers to the extent to which salespeople perceive the ST training provided by the selling organization to be effective. Training is an important part of internal company ST support (Hunter and Perreault 2006). At the same time, sales representatives respond to signals from their customers, so it is logical that customer IT expectations would result in greater use of ST by the salesperson. Although we hypothesize that customer IT expectations and ST training support both positively influence the three technology uses (accessing, analyzing, and communicating), we expect differential effects. Despite sellers' investments in ST training and regardless of what areas the training emphasizes, customers' IT expectations will be more influential in shaping technology uses by individual sales representatives. Extending this logic, we posit that customers will place more emphasis on analyzing and communicating than on accessing because these uses have the greatest impact on relationship-forging tasks and thus provide the greatest returns to the customer.

H_7: Customer IT expectations improve (a) accessing, (b) analyzing, and (c) communicating information.

H_8: ST training improves (a) accessing, (b) analyzing, and (c) communicating information.

Research Methods

Sample

To meet the objectives of this research, we needed to obtain details from sales representatives, which in turn required the cooperation of a firm's management. We selected a host firm using criteria and procedures that we developed on the basis of interviews with sales managers from different industries and a previous study of ST use in a different firm. Specifically, we focused on identifying a sales organization in which (1) salespeople conducted typical internal and external B2B sales tasks (e.g., they did not sell to final consumers), (2) ST was already implemented, (3) use of technology and technology skills varied across salespeople, (4) the sales force was large enough to support statistical tests of the hypothesized relationships, and (5) management would encourage participation in responses that would be kept confidential to researchers.

On the basis of these criteria, we approached managers at a well-known consumer packaged goods company (with which we had no prior connection). The managers were interested in the research questions and agreed to cooperate. They asked for (1) confidentiality, (2) limits on the time required from salespeople, and (3) inclusion of questions of interest to management (about the firm's ST training program). We pretested the questionnaire for clarity and completeness with the help of sales managers within the host firm and refined the directions and wording as appropriate. To ensure a high response rate, the firm's top sales executive sent each salesperson a prenotification letter that encouraged participation and a cover letter with the questionnaire. The letter and questionnaire guaranteed confidentiality to each salesperson. To signal anonymity of responses further, we sent questionnaires to the sales representatives' home-office addresses and asked them to return completed questionnaires directly to the researchers' university address. Of 196 questionnaires delivered, respondents returned 154 (79%). We subsequently dropped three questionnaires because of missing data, for an effective response rate of 77%.

The sample included both men (66%) and women. The average age was 42, but ages ranged from 23 to 63 (with sales experience ranging from new hires to 38 years). Respondents' annual salaries ranged from $24,000 to $139,000, and every respondent received some incentive or bonus income. On average, sales representatives worked 47 hours a week: 17 hours completing administrative and/or account coordinating responsibilities, 16 hours interacting with customers, 7 hours conducting data analyses, and the remaining 7 hours doing other activities.

A consumer packaged goods company provides a good context in which to test our model. As with most consumer packaged goods producers, the company's sales force is organized to handle efficient consumer response selling efforts and category management initiatives in the mass-merchandiser and supermarket channels. These efforts often involve the use of ST tools that help sales representatives harvest analytical "consumer insights," and many firms have in-house ST specialists who seek ways to use IT to improve selling functions. Sales representatives often make proposals pertaining to the retailer's category management decisions, including which stockkeeping unit to carry, shelf space allocations, promotion emphasis and timing, and so forth. Thus, within this context, an integrative solution proposed by a sales representative is one that considers the interests of both the retailer and the manufacturer.

Measures for Constructs

The questionnaire development relied on conventional procedures (DeVellis 1991) and employed SEM confirmatory factor analytic techniques to develop multi-item composite measures from a pool of items that represent the constructs in the conceptual model (Figure 1). Table 1 presents the scale items, response cues, and relevant statistics for each of the measures.

We developed the measures for the three types of ST use, the two relationship-forging tasks, customer expectations, and training effectiveness specifically for this study. To measure the key aspects of performance, we adapted scale items for administrative performance and relationship-building performance with customers from the rich literature on sales performance and blended them with new items to reflect the modern demands on salespeople.

The scale for relationship-building performance with customers comprises two items we took from Behrman and Perrault's (1982) scale that measures sales presentations and working well with customers. On the basis of consistency with our conceptualization and the resulting psychometric properties, we combined these two items with three new items. The two adopted items were "listening attentively to identify and understand the real concerns of your customers" and "working out solutions to a customer's questions or objections," and the three new items were "building your customer's business with your products," "working with customers to help them improve their profitability," and "working with buyers to develop a partner-

TABLE 1
Scale Items and Scale Statistics

Construct Name and Items	M	SD	Alpha Reliability	Construct Reliability	Item Reliability
Aspects of Sales Performance					
Relationship performance with customers[a]	5.36	.94	.82	.82	
Listening attentively to identify and understand the real concerns of your customers.					.62
Building your customer's business with your products.					.54
Working out solutions to a customer's questions or objections.					.53
Working with customers to help them improve their profitability.					.43
Working with buyers to develop a partnership that's profitable to both firms.					.28
Administrative performance[a]	5.80	1.09	.90	.90	
Getting required "paperwork" done.					.81
Addressing my administrative responsibilities in a timely manner.					.75
Submitting required reports on time.					.68
Categories of Sales Technology Use					
Using sales technology to access information[b]	4.80	1.35	.90	.90	
"Routine" to "sporadic"					.86
"Frequent" to "infrequent"					.75
"A major emphasis" to "not a major emphasis"					.73
"Hesitant" to "confident"[c]					.45
Using sales technology to analyze information[b]	4.34	1.42	.93	.93	
"Routine" to "sporadic"					.89
"Frequent" to "infrequent"					.86
"A major emphasis" to "not a major emphasis"					.88
"Hesitant" to "confident"[c]					.42
Using sales technology to communicate information[b]	5.14	1.36	.92	.92	
"Routine" to "sporadic"					.88
"Frequent" to "infrequent"					.88
"A major emphasis" to "not a major emphasis"					.77
"Hesitant" to "confident"[c]					.47
Relationship-Forging Tasks					
Proposing integrative solutions[d]	5.64	.86	.74	.74	
I'm good at finding opportunities that benefit both my firm and my customers.					.55
I try to solve customer problems in ways that also help my firm.					.46
I look for good ways to integrate my customer's goals with my company's needs.					.46
Sharing market knowledge[a]	4.88	1.03	.71	.71	
Others in my firm look to me for expert advice.					.55
Staying abreast of changes helps me keep my buyers informed.					.54
I keep my buyers aware of market changes.					.29
Compared to other salespeople, I'm not the most knowledgeable resource on our markets.[c]					.20

TABLE 1
Continued

Construct Name and Items	M	SD	Alpha Reliability	Construct Reliability	Item Reliability
Sales Context Conditions					
Customer's information technology expectation[d]	4.23	1.24	.83	.84	
The buyers I deal with use information technology and expect me to.					.70
The buyers I deal with encourage me to support my proposal with data.					.65
The buyers I deal with see value in using information technology to improve decisions.					.51
The buyers I deal with can't be satisfied unless I rely on information technology.					.40
The buyers I deal with don't expect me to use technology.[c]					.30
Sales technology training effectiveness[d]	3.87	1.26	.83	.83	
I have had effective training on sales technology tools.					.65
My sales technology training has been "world class."					.59
This firm needs to revamp its sales technology training programs.[c]					.50
Sales technology training in this firm is effective.					.47

[a] Respondents were directed, "On each of the following items, please rate how well you have performed relative to the average salesperson in similar selling situations," with seven-point response cues ranging from "needs improvement" (1) to "outstanding" (7).

[b] Respondents were asked, "Compared to other salespeople, my use of sales technology to (access, analyze or better understand, or communicate) information about products, sales calls, orders, sales, accounts, and the like, is best described as…." (1 indicated the leftmost descriptive response, and 7 indicated the rightmost response)

[c] Responses to this item were reverse scored.

[d] The seven-point response cues for each item ranged from "strongly disagree" (1) to "strongly agree" (7); note that fit statistics based on chi-square are not applicable for a construct with three indicators. For a more conservative test of convergent and discriminant validity, confirmatory factor analyses results for each of the blocks of constructs in the model appear in Table A1

Notes: We measured work experience by asking respondents, "How many years of experience do you have at your company and others?" Its mean was 18.2 (SD = 8.6). We measured effort by asking, "On average, approximately how many hours per week do you spend, in total, working in your sales job?" Its mean was 46.0 (SD = 13.3). We calculated alpha reliabilities for the constructs using Cronbach's algorithm for estimating the scales internal consistency, and we estimated the construct reliabilities using Fornell and Larcker's (1981) recommendations

ship that's profitable for both firms." Collectively, these five items capture the domain of the construct.

The scale for administrative performance combines two new items with one item that we adopted from Behrman and Perreault's (1982) scale for providing information. The adopted item is "submitting required reports on time," and the two new items are "getting required 'paperwork' done" and "addressing my administrative responsibilities in a timely manner."

Although many previous studies (see Leigh, Pullins, and Comer 2001; e.g., Oliver and Anderson 1994; Sujan, Weitz, and Kumar 1994) used or adapted items from Behrman and Perreault's (1982) scale to measure sales performance, it would have been desirable here to include customer evaluations of sales representatives' relationship-building performance. However, management would not allow us to contact customer accounts, among other reasons because many supermarket chains have policies that restrict buyers from responding to *any* request for evaluation by a vendor. Similarly, the firm did not have a formal system in place for evaluating the administrative performance of individual representatives. Such obstacles are common in research on sales performance.

Data Analysis Methods

Data analysis for this study is based on SEM with maximum likelihood parameter estimation. We used the two-step approach that involves evaluating measures and then estimating the proposed structural model (e.g., Anderson and Gerbing 1988). Specifically, we fit a separate confirmatory factor model for each of the proposed scales to assess reliability and convergent validity. Next, to assess discriminant validity, we fit confirmatory factor analysis models to items for sets of scales that were most susceptible to cross-loadings (i.e., sets of constructs within each block in the proposed model). We then extended the confirmatory factor analysis models to test items across sets of scales that constitute the proposed subsystems in the model (e.g., relationship-building performance with customers and administrative performance).

Because the number of items is large, we test the fit of the overall structural model and the statistical significance of the hypothesized effects by using scale scores (based on the average of the individual items) for the latent constructs. With this approach, the standardized effect of measurement error for a scale is equal to the square root of the reliability estimate. The error variances are equal to the product of the scale variance and one minus the scale reliability.

The structural model in Figure 1 is a block-recursive model. This means that it contains "conditions under which the endogenous variables that are determined by one subsystem are exogenous relative to those that are determined by another subsystem" (Bekker and Pollock 1986, p. 180). We formed the first block (subsystem) in the model by freeing covariance parameters across the three types of uses and the second block (subsystem) by freeing covariance parameters across the two relationship-forging tasks. Estimation of the effects for individual constructs (and fit) based on a block-recursive model requires model identification; yet some structural models published in marketing are not properly identified. To avoid this problem, we established that our proposed model is identifiable by using an algebraic approach recommended in the econometric literature (Bekker and Pollock 1986; Bollen 1989).

We propose single-, double-, and triple-mediated indirect effects, but it is important to emphasize that we are not proposing a saturated model. On the contrary, the model explicitly includes 30 direct effect relationships between constructs that are constrained to be zero. For example, there are 4 separate zero-constrained relationships between using technology for accessing information with the two relationship-forging tasks and the two aspects of performance. We do not discuss all the zero-constrained effects in detail in this article, but we test them all and report statistical results along with our tests for the formally presented hypotheses. Thus, the relationships we specify as involving no effect are logically part of our theoretical rational.

Results

Evaluation of Measures

It is useful to confirm the psychometric properties of the measures before we consider the fit of the overall structural model and tests of the hypothesized relationships. The constructs correlate with other study variables in expected directions, suggesting their content validity (Fornell and Larcker 1981). The construct reliability indexes in Table 1 are based on the shared variance between the (observed) items and the underlying latent construct (for computational details, see Fornell and Larcker 1981). Bagozzi and Yi (1988) suggest that it is desirable for this construct reliability index to be greater than .6, and the estimates for all the constructs here exceed .71. Similarly, the item reliability estimates in Table 1 are equal to the proportion of variance in an item explained by its proposed latent construct. Conventionally, in marketing research, item reliabilities lower than .15–.20 (or, equivalently, squared multiple correlation coefficients less than .38–.45) imply that an item may not be internally consistent (for a discussion, see Bollen 1989, Chap. 6; see also Bollen and Lennox 1991). In this study, in general, these items exceed these criteria. Here, the lowest item reliability is .20 (one of the reverse-scored items, which usually has lower reliabilities but is included to improve scale design). Anderson and Gerbing (1988) offer the guideline that there is convergent validity among items for a construct when their estimated factor coefficients are greater than two times the associated standard error. All our constructs and items exceed these criteria, providing evidence for construct reliability and convergent validity. Deleting items with low reliabilities would increase some of the scale reliability indexes. However, removing psychometrically acceptable items may weaken content validity and narrow the domain of the construct (Gerbing, Hamilton, and Freeman 1994).

We computed model comparisons to evaluate discriminant validity and the potential threat to validity because of common method bias. The results of these analyses appear in the Appendix. Evidence from all these analyses support the discriminant validity of the measures. In addition, the average extracted variances for all scales exceed each scale's squared correlations with other study constructs, in support of the discriminant validity of the constructs (Fornell and Larker 1981). Similarly, although method bias is always a potential problem with self-report (survey) data, evidence suggests that it does not affect the results of this study.

Overall Model Fit and Relationships Among Constructs

Figure 2 provides a summary of the maximum likelihood estimates (and associated probability levels) for all the hypothesized relationships. These estimates are based on an overall structural model that produces evidence of an excellent overall fit. The chi-square statistic is not significant ($\chi^2 = 37.1$, d.f. $= 30$, $p = .17$), and thus there is not evidence to reject the hypothesized relationships or model structure. Other fit statistics appropriate for this model (Bollen 1989) provide consistent evidence of a good fit: comparative fit index (CFI) = .98, root mean square error of approximation (RMSEA) = .04, goodness-of-fit index (GFI) = .96, and adjusted goodness-of-fit index (AGFI) = .91. Consistent with these overall fit statistics, the path coefficients for all but one of the hypothesized relationships specified in the model are statistically significant ($p < .05$), though one is in the opposite direction from our hypothesis. In addition, as the R-square values in Figure 2 show, the model provides good explanatory power for the individual endogenous variables.

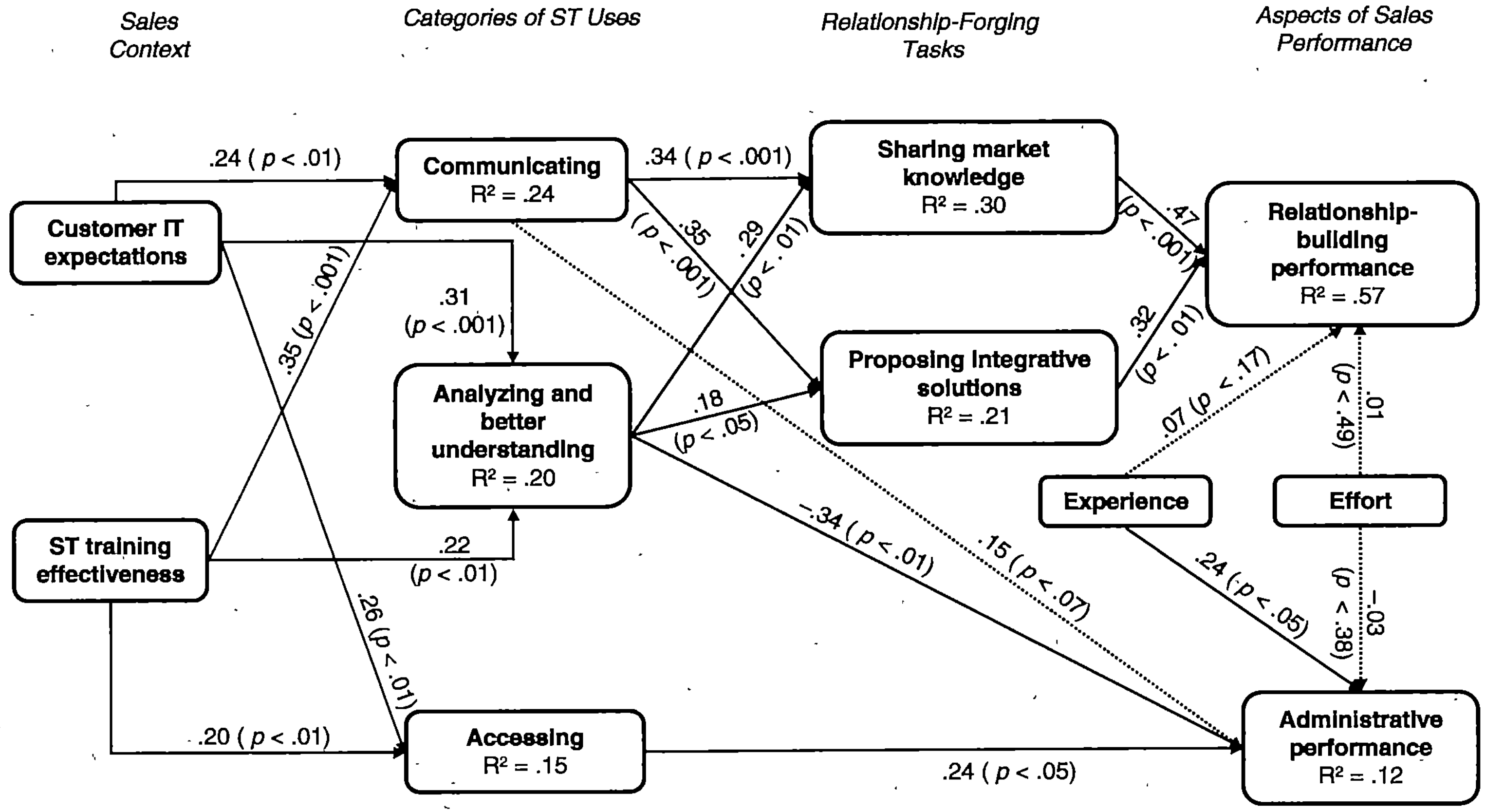
The estimates and overall fit statistics developed for the structural model are based on maximizing the fit between the covariance structure we predicted for the structural relations and the overall matrix of observed sample covariances. Thus, the (bivariate) product correlations between constructs in the model (see Table 2) are a useful supplement to the (multivariate) information in Figure 2. Subsequently, we review the results for individual hypotheses using the order we used to introduce them.

Relationship-Building Performance with Customers

The path coefficients for sharing market knowledge and proposing integrative solutions are each statistically significant ($p < .01$), and in combination, they explain more than half of the variance in relationship-building performance with customers. The larger path coefficient for sharing marketing knowledge (.47) suggests that it has a greater impact on relationship-building performance with customers than does proposing integrative solutions (.32). In combination, this is a strong prediction compared with previous studies that have considered other role-related factors that influence sales performance, and it confirms that relationship-forging tasks warrant managerial and scholarly attention.

Note that the model specifies that there is no direct relationships between the different uses of ST and relationship-

FIGURE 2
Maximum Likelihood Estimates (with Probability Levels) and R-Square Values for Paths in the Block-Recursive Structural Model



Notes: Fit statistics suggest an excellent fit for the overall model: ($\chi^2 = 37.1$, $p = .17$, d.f. = 30; CFI = .98; RMSEA = .04; GFI = .96; and AGFI = .91). Solid lines indicate statistically significant effects, based on probability values for one-tailed significance effects on path coefficients. Although correlations across blocks are not shown in the diagram, the estimates are based on a block-recursive model, which estimates and accounts for correlations among constructs within blocks; the correlation estimates within blocks are .34 between customer IT expectations and ST training effectiveness, .31 between communicating and analyzing, .37 between communicating and accessing, .68 between analyzing and accessing, .71 between the relationship-forging tasks, and .48 between the two aspects of performance.

TABLE 2
Correlations Among Measures for Constructs in Model

	Product Moment Correlations									
Measures	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. Training effectiveness	1.00									
2. Customer's IT expectations	*.29*	1.00								
3. Using ST for accessing	*.25*	*.29*	1.00							
4. Using ST for analyzing	*.29*	*.34*	*.67*	1.00						
5. Using ST for communicating	*.38*	*.32*	*.44*	*.42*	1.00					
6. Proposing integrative solutions	*.29*	.12	*.21*	*.29*	*.36*	1.00				
7. Sharing market knowledge	*.24*	*.21*	*.30*	*.38*	*.39*	*.56*	1.00			
8. Sales experience	–.03	.04	–.03	–.03	.03	.12	.06	1.00		
9. Total work effort	–.06	*–.17*	.02	–.06	.11	.03	.01	.10	1.00	
10. Internal administrative performance	.01	–.10	.06	–.09	.09	*.20*	.13	*.23*	.01	1.00
11. Relationship-building performance with customers	.08	.03	*.21*	*.26*	*.26*	*.57*	*.57*	.13	.03	*.36*

Notes: Correlation coefficients with magnitudes greater than .16 result in a statistically significant t-test (probability less than or equal to .05) and appear in italics

building performance with customers. This equates to constraining the value of these paths to zero in fitting the model. Thus, these results support the proposition that it is primarily through relationship-forging tasks that ST influences relationship-building performance with customers.

Relationship-Forging Tasks

The model proposes that STs used for analyzing and communicating information, but not for accessing information, affect relationship-forging tasks. The resulting estimates are consistent with this logic. Sales technologies for both communicating and analyzing are statistically significant in predicting each of the relationship-forging tasks. Prediction for sharing marketing knowledge is slightly stronger (30% of the variance versus 21% for proposing integrative solutions). The path coefficients suggest that communicating and analyzing have roughly equal impact on sharing market knowledge (coefficients of .34 and .29, respectively) but that STs for communicating (.35) are more important than analyzing (.18) in proposing integrative solutions.

The relationships in the model are based on the logic that accessing information is not a salient factor in relationship-forging tasks if communicating and analyzing technologies are considered. The overall model fit, which explicitly excludes the link between accessing and the relationship-forging tasks, supports this proposition. Furthermore, the SEM modification index for the hypothesized zero effect of using technology for accessing information is .03 for its effect on sharing market knowledge and .20 for its effect on proposing integrative solutions. Both indexes are well below Sörbom's (1989) suggested cutoff of 5 for statistical significance.

The strong effects among the relationship-forging tasks and the two categories of technology uses—communicating and analyzing—outline a prominent process through which sales representatives can leverage information to forge relationships with customers. Conversely, using technology to access information does not directly aid sales representatives' efforts in forging relationships, unless it occurs through a mediated process. Such a mediated effect can be represented through the block-recursive model specification. Specifically, the relationships among the three types of ST uses (within the block) represent a means through which such mediation might occur. However, we do not advance (or test) directional hypotheses about the relationships between the different uses of technology, because the block-recursive specification more accurately reflects the interactive and potential feedback loops across types of use.

Administrative Performance

The positive path coefficient (.24) for the effect of accessing information on administrative performance is statistically significant ($p < .05$) and consistent with the hypothesized logic. However, the path estimates for the other two uses of technology deviate from our hypothesis. First, the relationship between using ST for communicating and administrative performance (.15) is not statistically significant. Even more surprising is the statistically significant, negative effect (–.34, $p < .01$) of using ST for analyzing on administrative performance. This finding could mark a time tradeoff that may occur between conducting thorough data analyses and spending time on administrative matters (e.g., submitting required reports on time).

This pattern of results is provocative when we contrast it with the way that using technology for communicating and for analyzing affects the relationship-forging tasks and, in turn, the salesperson's relationship-building performance with customers. There is a positive, contemporaneous relationship (.48) between the different aspects of performance. Thus, consistent with the conventional argument for adopting SFA, using ST to increase administrative performance may contribute to increased relationship-building performance with customers. Conversely, there may be a time-use conflict pertaining to the use of ST for analyzing. Analyzing positively influences relationship forging, but because analyzing tends to be time consuming, it may distract the sales representative from administrative work. This also implies that transferring extra administrative work to the representative (even if it can be performed more efficiently with technology) tends to interfere with some aspects of the relationship-forging process.

Technology Uses

Although the focus of this research is on different uses of ST, relationship-forging tasks, and sales performance, the model also considers how the sales context influences sales representatives' use of ST. Consistent with the hypothesized model, each technology use is positively affected (encouraged) by both the firm's sales training effectiveness and customer IT expectations. It is informative that these two influences on sales representatives have differential effects. For example, in the structural model (Figure 2), antecedents explain 24% of the variance for using technology for communicating; training effectiveness has a path coefficient (.35) that is roughly 50% larger than the coefficient for customer IT expectations (.24). For use of ST for analyzing, the explained variance is slightly lower (15%). Customer IT expectations has the larger coefficient (.31 versus .22 for the firm's sales training effectiveness). Finally, the path coefficients for prediction of accessing information are more similar in size (.26 for customer IT expectations and .20 for ST training effectiveness), but the explained variance is lower.

The results of this model provide a means for estimating the technology–sales performance relationships. In SEM, the total effects of independent variables on a dependent variable can be estimated by summing its statistically significant indirect and direct effects (Bollen 1989). Table 3 summarizes the effects.

Finally, in mediated models, it is useful to test zero-constrained relationships in mediated models. Sörbom (1989) suggests the use of modification indexes for this purpose. The small modification indexes we observe in this study provide evidence that helps rule out several alternative models and increase confidence in the behavioral process that we propose and test. In addition, many of tests of "no relationship" among constructs in the model have never previously been tested or reported in the literature (in some cases, because the constructs are new to this study).

Discussion

This research provides managers and scholars with a better understanding of the important role of ST in helping salespeople forge relationships with business customers while considering its effects on administrative performance. Here, we contribute theory and evidence about new behavioral mechanisms (relationship-forging tasks) through which different dimensions of IT use (accessing, analyzing, and communicating information) influence key aspects of a salesperson's performance. Using SEM approaches to estimate a proposed block-recursive model, we evaluate the simultaneous (multivariate) relationships among different categories of ST uses and the mechanisms by which they are related to sales performance. In this section, we discuss this study's managerial implications, research implications, and limitations.

Managerial Implications

The sales force and ST represent important parts of a firm's value creation potential. Rackham and DeVincentis (1998) argue that the classic view of firm strategy posits that the value-creation function of marketing is through product and brand innovation but that the sales function's role is limited to value communication. Rackham and DeVincentis contrast that view with the realities of the new relational selling (and the vital role that sales people can play in value creation by providing services that differentiate the firm's offering), calling it "the new marketing myopia" (p. 9).

TABLE 3
Standardized Total Effect (Based on Sum of Direct and Indirect Effects) for Each Independent Variable on Each Dependent Variable

	Dependent Variable for Each Path Estimated in Overall Model						
Independent Variable	**Using ST for Accessing**	**Using ST for Analyzing**	**Using ST for Communicating**	**Proposing Integrative Solutions**	**Sharing Market Knowledge**	**Internal Administrative Performance**	**Relationship-Building Performance with Customers**
Training effectiveness	.20	.22	.35	.16	.19	.03	.13
Customer's IT expectations	.26	.31	.24	.14	.15	.00	.12
Using ST for accessing						.24	
Using ST for analyzing				.18	.29	−.31	.18
Using ST for communicating				.35	.34	.15	.24
Proposing integrative solutions							.29
Sharing market knowledge							.43
Sales experience						.24	.07
Total work effort						−.04	.01

This new value-creating aspect of a B2B sales representative's job often demands data-driven activities (e.g., proposing integrative solutions), which in turn alter the skills required of an effective salesperson. For example, salespeople in the channels use sophisticated analytical models and marketing research insights to compare forecasts from alternative marketing strategies for their customer accounts. Thus, the representative's capacity to use a portfolio of ST tools is tested over time as customer accounts monitor the results attained from the representative's recommendations. Salespeople whose recommendations are beneficial to both the producer and the retailer add incremental value and help forge the buyer–seller relationship. Thus, such relational selling processes create value and help differentiate the seller's offering.

Marketing and sales strategists should consider the new realities of relational selling in an information-intensive environment because it drives the importance of ST. A means for adapting strategic market plans to reconsider ST and relational selling tasks involves redefining the sales force not only as part of the promotion mix but also as an important part of the firm's product. When a product is viewed as the "need satisfying offering of a firm," customers evaluate the offering on the basis of the total satisfaction it provides (Perreault and McCarthy 2005, pp. 242–43). Thus, sales representatives represent an important means for achieving total satisfaction by differentiating the firm's offering. For example, Procter & Gamble, IBM, and several other firms rely on this sales service differentiation and consultative selling to provide superior value to their customers. An important precursor to delivering high-quality consultative sales services is the representative's relationship-building performance with customers. However, more theorizing and research is needed to evaluate how relationship-forging tasks and relationship-building performance influence customer value.

Broadly speaking, this study offers a flexible framework ("template") for diagnosing how different uses of technology affect sales performance through salesperson behaviors. Applied in other sales organizations, the model specification could be expanded to include other relevant antecedents, technologies, and criterion variables. For example, the specification might be broadened to include buyer reactions to specific salesperson behaviors and overall satisfaction with the services the sales representative provides.

Adopting ST requires thoughtful consideration of potential trade-offs. Our results raise a caveat about the widespread emphasis on adoption of SFA or CRM tools to make the sales force more efficient. Gains in efficiency will have a net positive effect only if they free sales representatives from time spent on nonselling activities and if the representative redirects that incremental time to tasks that improve relationship-building performance with customers (i.e., relationship-forging tasks). As firms begin to shift more administrative work (e.g., record keeping) to sales representatives, there is a risk of miscalibrating the opportunity cost. When the time spent on "efficient" administrative work is increased, it will still take time that sales representatives could use for customer-related responsibilities. Most people, sales representatives included, have a "time budget" that they devote to their jobs. In this study, representatives spent two-thirds of their 47 weekly hours on the job doing things other than interacting with customers (or "communicating value").

This research has a potential impact on organizational structure. The focus here is not on the functions of specific technologies but on the impact of different dimensions of technology use on the sales process. This is a simple, but important, distinction from the way managers and scholars traditionally think about the ST issue. The importance of this distinction rests in the manager's control over both investments in technology and design of work processes. That is, managers should not limit attention to technologies that influence existing work processes but rather should expand this consideration to uses of technology that enable sales representatives to provide value in new ways. This may require redesigning work processes and changing organizational structure, but it has the potential to help a firm realize strategic gains (including relationship building) through technological innovations. The different abilities required by sales representatives to make this work will obviously create new demands for hiring and training salespeople, which helps explain why hiring and training are currently two of the most important factors for sales force success (e.g., Zoltners, Sinha, and Zoltners 2001, p. 161).

Research Implications

The concept of relationship-forging tasks represents an important new theoretical perspective for future research in interorganizational contexts. We test relationships in terms of two key relationship-forging tasks that are influenced by ST uses: sharing market knowledge and proposing integrative solutions. However, a broader view suggests that theorizing about and evaluating other types of relationship-forging tasks would be useful for both scholars and managers. For example, our interviews with salespeople and sales managers suggest that relationship-oriented sales planning, coordinating activities across complex buyer–seller interfaces, and serving as a real advocate for the customer within the selling firm are other potentially important relationship-forging tasks.

The results from this research suggest that relationship-forging tasks represent new "smart-selling" behaviors in a relational context. There is a rich sales literature on working smarter versus working harder (Sujan, Weitz, and Kumar 1994) that shows the important effects of adaptive selling and sales planning on sales performance. Instead of testing traditional smart-selling behaviors (planning and adaptive selling), our model proposes relationship-forging tasks as predictors of sales performance while controlling for the effects of working harder (total effort). These new smart-selling behaviors (proposing integrative solutions and sharing market knowledge) explain more than half of the variance in relationship-building performance with customers; notably, working harder has no statistically significant effect. These findings suggest an alternative model of smart selling in relational contexts. Simply working harder (putting in more time at work) might not help a salesperson build better relationships with customers, unless the sales-

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person devotes that incremental time to performing relationship-forging tasks. Although sales experience is positively related to administrative performance, its effect on relationship-building performance with customers is not statistically significant. One possible explanation for this that is consistent with our theorizing is that changes in the sales role are so dramatic that salespeople with pre-relational-selling-era experience realize minimal advantages over their less experienced counterparts, given equivalent practices of relationship-forging tasks. In other words, ST may serve as an experience multiplier for less experienced representatives.

Different uses of technology have differential effects on various aspects of performance. This study builds on Huber's (1991) and Sinkula's (1994) research on organizational learning by focusing on different dimensions of technology use, thus going beyond testing technology use as a one-dimensional construct. Moreover, consistent with the logic of Goodhue's (1995a, b, 1998) task–technology fit theory, we find differential effects across types of uses on different behavioral tasks (and aspects of performance). This evidence supports our logic that technology use influences relationship orientation through a mediated process—namely, the salesperson's conduct of relationship-forging tasks. Thus, how a sales representative uses technology and on which behavioral tasks (work processes) matters.

Without an understanding of the ST–performance relationship, sales managers may increase ST costs but decrease potential returns. Evidence from this study supports the view that using technology for analyzing and/or communicating information positively affects sharing marketing knowledge and proposing integrative solutions, but using technology for accessing information has no effect on relationship-building performance with customers. Similarly, using technology for accessing and analyzing information has direct effects on administrative performance, but the effect on administrative performance from using technology for communicating information is not statistically significant, and using technology for analyzing information has a negative impact on administrative performance.

Training and buyer encouragement represent relevant social influences on technology use that may be in conflict with each other. Building on social influence theory (Fulk 1993), we suggest that two important social players—buyers and managers—influence the salesperson's use of ITs. Our evidence suggests that sales representatives' technology use is responsive to encouragement from both their own firms and their customers. However, the two firms' priorities may differ. Specifically, the firm's training may put more emphasis on use of ST for communicating, whereas customers who have high IT expectations reinforce more use of ST for analyzing. Such differences represent a source of role conflict for B2B salespeople; this warrants further managerial and scholarly attention.

Limitations

This study has various limitations that should be considered. Although many published studies rely on self-reported measures of sales performance (e.g., Anderson and Robertson 1995; Behrman and Perreault 1982, 1984; Cravens et al. 1993; Jaramillo, Mulki, and Marshall 2005; Oliver and Anderson 1994; Singh 1998; Sujan, Weitz, and Kumar 1994), there is always a potential for common method bias. Here, we conduct and report an analysis (see the Appendix) that provides evidence that suggests that our estimates are not biased by our reliance on self-reported data. Nonetheless, it would have been desirable to include other reliable quantitative measures of sales performance or profit contribution provided by the company; however, management would not release propriety sales measures on individual accounts. Conversely, the solution is not as simple as using sales volume or other quantitative metrics when they are available. Although in contemporary sales performance research some scholars imply that quantitative measures are objective, Russell (1950) expressed concern about the true "objectivity" of quantitative measures when he proposed them for sales analysis more than a half century ago. For example, there are differences in territory and account potential unrelated to the efforts of the current sales representative (Behrman and Perrault 1982), including factors such as market potential, territory workload, and the company's reputation within the territory (Cravens, Woodruff, and Stamper 1972). Zoltners, Sinha, and Zoltners (2001) also outline how a selling organization's investments in other go-to-market participants (e.g., advertising and promotion, call centers and telesales, the Internet) influence company results. Nonetheless, in some situations, quantitative measures can be used (and adjusted, as appropriate, for factors beyond the control of the salesperson). Although quotas can be used to adjust quantitative measures and make them more objective, they are also imperfect. In our case, the host firm does not use them for this reason. Perhaps more important, there is a growing practice in relational selling contexts to emphasize long-term relationship-building performance measures over short-term quotas. Sales organizations often include self-evaluation or customer evaluation as a component for evaluating salesperson performance. Finally, the use of self-reports makes research easier to replicate within and across sales organizations, including international contexts (Atuahene-Gima and Li 2002). Thus, self-reported measures of performance have both advantages and limitations.

We evaluate a buyer–seller relationship on the basis of the seller's view, but this research could have benefited from additional measures based on buyer's inputs. Although the host firm in this research did not want to solicit inputs from buyers, it would be useful to have evidence of whether the seller and buyer share a common perspective.

Consumer packaged goods firms may be at the forefront of ST implementations. Consequently, the results from our host firm may reflect "best practices" in ST implementation rather than what a start-up would experience. However, the host firm's use of technology may foreshadow adoption and implementation issues that other firms may confront as information availability, category management practices, relational selling, and ST infuse across other industries and firms. Moreover, the process model approach we use, which focuses on evaluation of the intermediate outcomes of different aspects of ST, readily applies to other contexts in which IT influences how people work. In essence, the approach provides a means for managers and scholars to supplement other examinations of the interrelationships among people, processes, and technologies in an integrative, holistic fashion.

Further Research

Additional research on ST and relationship-forging tasks is needed. Marketing scholars and managers have an important role to play in the ever-expanding domain of ST. To date, many key decisions about what technologies to develop (or buy) have been guided primarily by IT specialists rather than by marketing/sales experts. Although technologies must be properly implemented and support needs to be effective, it is also important that resources be put into solving the right problems and performing the right tasks. If marketing managers do not play an active role in the dialogue about which STs are needed, revenue generation opportunities may be lost. For example ST decisions benefit from marketing knowledge about organizational procurement processes (see Hunter, Bunn, and Perreault 2006) and how such buying tasks can best be integrated with sales processes. Research is needed to guide these decisions, which often have huge financial implications.

Research into the antecedents of effective ST use would improve the understanding of how best to recruit, motivate, and train salespeople for new relational selling roles. There is a pressing need for better understanding of salesperson preferences for various training methods, the effectiveness of those methods, and how best to support organizational learning for sales forces. Many companies yield to cost pressures (and IT "norms") when they rely primarily on online help systems to support new ST tools, but this seems to ignore Rogers's (1962) basic caveats about how compatibility affects adoption of innovations. With online help, it is likely that sales representatives who are least comfortable with software and who find it most incompatible with their sales style confront a training approach that is also incompatible with their established ways of learning. Similarly, a better understanding of factors that influence customer expectations about technology uses would be helpful.

Conclusion

Sales technology is an area in which scholarly guidance for management decisions has been sparse, even though it is expensive, difficult to manage, and fast changing. Despite the challenges associated with understanding relationship-forging tasks and ST, their importance to practice warrants additional research. There is a need for marketing scholars (not just researchers who take an information system perspective) to continue to improve conceptualization and theory in this arena. New ST tools are needed to help representatives develop solutions that meet customer needs, and technology should not be considered by managers as just another means for cutting selling costs (or displacing the sales force altogether). To evaluate such trade-offs, there is a need for better methods of evaluating and diagnosing what is (and is not) the best use of ST for achieving strategic objectives.

Appendix

Discriminant Validity of Measures

Our conceptual model includes subgroups of constructs (e.g., the different uses of ST or the different aspects of performance) that are expected to be empirically related. Nevertheless, these sets of constructs (and the items on which they are based) must exhibit discriminant validity, or interpreting results from the block-recursive structural model would be inappropriate. Therefore, to assess discriminant validity of the ST uses, relationship-forging tasks, and the aspects of sales performance constructs, we tested three sets of models. The models represent alternatives to the proposed blocks among the constructs and items.

The first set of tests compares the hypothesized multifactor structure for constructs within a block with a one-dimensional factor (i.e., all items in the block are related to a single factor). The second set of tests examines the fit of a higher-order factor (i.e., individual factors for constructs within a block also combine to form a second-order construct). The third set of tests compares a model with uncorrelated factors with the proposed model that assumes relationships among constructs in the block.

To test one-dimensional factor model alternatives, we compared the fit of a single-factor model with the proposed multidimensional model (Anderson and Gerbing 1988). Because this involves comparisons between nonnested models, we computed fit statistics for each model and then (as Bollen [1989] recommends) favored models with the highest CFI, an index designed to compare nonnested models. Because models for the higher-order factor comparison and the uncorrelated constructs comparison involve conventional tests of nested SEM models (i.e., constraints are imposed on the proposed models), we used the chi-square-difference test. In all cases, the statistical evidence supports the proposed models (for details, see Table A1).

To assess the discriminant validity of the items further, we compared each item's correlation with a composite of the remaining items that constitute its scale with that same item's correlations with all other scales in the proposed model. In only one case was an item's correlation with an unintended scale higher than its correlation with its composite. The item "staying abreast of changes helps me keep my buyers informed" had a correlation of .52 with its composite versus a .55 correlation with the proposing integrative solutions scale. We kept the item to preserve the construct's content validity. Furthermore, all item-to-scale composites were .40 or higher, and the average minimum absolute value between items to intended composite and items to unintended scales was .24. In combination, these statistics provide strong evidence in support of the discriminant validity of the constructs and, in general, to the use of the block-recursive modeling approach we presented.

Evaluation of Potential Common Method Bias

With SEM, it is possible to test for the effect of common method bias among measures. We used two different approaches to test method bias. First, we fit a model with all manifest items loading on a single factor, representing a

TABLE A1
Confirmatory Factor Analyses Results and Comparisons with Alternative Models for Proposed Blocks of Constructs

	Proposed Block Versus One-Dimensional Alternative			Proposed Block Versus Higher-Order Alternative			Proposed Block Versus Unrelated Constructs Alternative		
Block	**CFI, AIC Proposed Block**	**CFI, AIC Alternative Model**	**ΔCFI, AIC**	**χ^2, d.f. Proposed Block**	**χ^2, d.f. Alternative Model**	**$\Delta\chi^2$ (p Value)**	**χ^2, d.f. Proposed Block**	**χ^2, d.f. Alternative Model**	**$\Delta\chi^2$ (p Value)**
Sales Context χ^2 = 29.3 (p = .30), d.f. = 26; RMSEA = .04; GFI = .98; and AGFI = .94	.99, 67.3	.22, 252	.37, –184	29.3, 26	45.2, 27	15.9 (<.001)	29.3, 26	50.0, 27	11.7 (<.001)
ST Uses[a] χ^2 = 66.2 (p = .00), d.f. = 39; RMSEA = .07; GFI = .93; and AGFI = .86	.98, 144.1	.55, 817	.47, –583	66.2, 39	189.6, 42	114.1 (<.001)	66.2, 39	177.3, 42	111.1 (<.001)
Relationship-Forging Tasks χ^2 = 13.8 (p = .39), d.f = 13; RMSEA = .02; GFI = .97; and AGFI = .94	1.00, 43.8	.89, 86.1	.11, –32.3	13.8, 13	25.5, 14	11.7 (<.001)	13.8, 13	79.2, 20	65.4 (<.001)
Aspects of Sales Performance χ^2 = 25.2 (p = .16), d.f. = 19; RMSEA = .05; GFI = .96; and AGFI = .92	.98, 59.2	.70, 456	.22, –130	25.2, 19	38.6, 21	13.4 (<.001)	25.2, 19	50.5, 20	25.3 (<.001)

[a] We specified correlated errors across like adjective pairs in both the proposed and the alternative models.

Notes: Fit statistics for confirmatory factor analyses of each of the proposed structural subsystems (blocks) appear beneath each block's title. AIC = Akaike information criterion common method influence. This model produced an extremely poor fit ($\chi^2 = 2694.0$, $p < .001$, d.f. = 595; CFI = .36; RMSEA = .15; GFI = .42; and AGFI = .35), providing evidence against the potential biasing effect of a common factor. Second, we tested for same-source bias by reestimating the proposed structural model, after including a common method first-order factor that we allowed to covary across each of the self-report scales. By constraining loadings to be equivalent across scales, we identified the model, which represents the effects of a potential omitted latent construct across the scales. Using a chi-square-difference test between nested models, our findings suggest that a same-source factor did not influence the overall model fit statistics ($\chi^2 = 34.3$, $\Delta\chi^2 = 2.8$, Δd.f. = 2, $p = .25$). In addition, we compared the standardized parameter estimates for the alternative models and noted that the estimates were similar in both cases. Thus, although method bias is always a potential problem with survey data, these tests provide evidence that it did not significantly influence the results from this analysis.

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Advertising, Research and Development, and Systematic Risk of the Firm

Marketing executives are being urged to speak in the language of finance to gain internal support for marketing initiatives. Responding to this call, the authors examine the impact of a firm's advertising and its research and development (R&D) on the systematic risk of its stock, a key metric for publicly listed firms. They hypothesize that a firm's advertising and R&D expenditures create intangible assets that insulate it from stock market changes, lowering its systematic risk. They test the hypotheses using a panel data on 644 publicly listed firms between 1979 and 2001, consisting of five-year moving windows. They scale the firm's advertising and R&D expenditures by its sales. After controlling for factors that accounting and finance researchers have shown to be associated with systematic risk, the authors find that advertising/sales and R&D/sales lower a firm's systematic risk. The article's findings extend prior research that has focused primarily on the effect of marketing initiatives on performance metrics without consideration of systematic risk. For practice, the ability of advertising and R&D to reduce systematic risk highlights the multifaceted implications of advertising and research programs. The article's findings may surprise senior management, some of whom are skeptical of the financial accountability of advertising programs.

There is a growing consensus that senior management and finance executives focus on maximizing shareholder value and do not value marketing performance metrics (e.g., awareness, sales growth, loyalty, customer satisfaction, repeat purchase), because they do not understand how or even whether these metrics are of interest to the firm's shareholders (Ambler 2003). Consequently, marketing executives are urged to "speak in the language of finance" with their finance colleagues and senior management (Srivastava and Reibstein 2005) because financial return is the dialogue required to access funds from the financial purse strings that are crucial for the implementation of marketing programs. To address this gap, in this article, we examine whether a firm's advertising and research-and-development (R&D) expenditures affect a metric of interest to both finance executives and senior management: the firm's "systematic risk," or β (we use these terms interchangeably throughout the article to denote the systematic risk of the firm's stock).[1]

Portfolio theory (Lintner 1965; Sharpe 1964), a key development in finance, posits that investors can diversify away a portion of the risk associated with a firm's stock by constructing a portfolio of stocks whose returns correlate imperfectly with one another. In equilibrium, the risk that is priced in the stock market is the stock's systematic risk, which is a function of the extent to which the stock's return changes when the overall market changes.[2] This market-driven variation in a firm's stock returns, which cannot be diversified away, is its systematic risk. By construction, the stock market, as a whole, has a β of 1.0. A stock whose return falls (or rises) more than the market's return falls (or rises) in response to a change in the market has a β greater than 1.0. If a stock's return falls (or rises) less than the market's return falls (or rises) in response to a change in the market, its β is less than 1.0. Thus, β, a measure of the stock's sensitivity to market changes, is an important metric for publicly listed firms.

In this article, we examine the relationship between a firm's advertising and R&D and its systematic risk. Recent developments in the market-based assets theory (Srivastava, Shervani, and Fahey 1998) suggest that a firm's advertising creates intangible market-based assets (e.g., brand equity) and that these assets strengthen performance—including sales growth, market share, and profitability (Boulding and Staelin 1995; Erickson and Jacobson 1992)—and shareholder value (Joshi and Hanssens 2004; Rao, Agarwal, and

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[1] As we discuss subsequently, to eliminate potentially confounding effects of firm size on systematic risk, in the empirical estimation, we scale the firm's advertising and R&D by its sales.

[2] Thus, β is measured as (covariance [stock and market])/(variance [market]).

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Dahloff 2004). We suggest that the consumer loyalty and the bargaining power over distribution channel partners inherent in these intangible market-based assets help insulate the firm from the impact of stock market downturns, thus lowering the firm's systematic risk. On the basis of developments in the finance literature, we propose another way that advertising-created market-based assets might affect a firm's systematic risk. Frieder and Subrahmanyam (2005, p. 57) note that because of increased firm awareness due to advertising, all else being equal, "investors prefer holding stocks with high recognition and consequently, greater information precision." Grullon, Kanatas, and Weston (2004) find that a firm's advertising results in broader ownership of the stock. We anticipate that this broader ownership may insulate the stock's return from market downturns.

Consistent with these theoretical developments, two recent studies (Madden, Fehle, and Fournier 2006; Singh, Faircloth, and Nejadmalayeri 2005) have explored the relationship between a firm's advertising and its systematic risk. Singh, Faircloth, and Nejadmalayeri (2005) report a significant, negative relationship between a firm's advertising and its systematic risk. Using a sample of "best-performing firms" from the Stern–Stewart database for the period between 1998 and 2001, Singh, Faircloth, and Nejadmalayeri find that greater advertising expenditure (operationalized as advertising dollars) is associated with lower systematic risk. Madden, Fehle, and Fournier (2006) compare the performance of three stock portfolios—a portfolio of firms with strong brands (using Interbrand's measure of brand strength), a portfolio of firms excluding firms with strong brands, and a portfolio of all firms—and find that the portfolio of firms with strong brands had higher returns and lower systematic risk than the other two portfolios.

Singh, Faircloth, and Nejadmalayeri's (2005) and Madden, Fehle, and Fournier's (2006) studies raise intriguing research questions: Will the negative relationship between advertising (or brand strength) and systematic risk hold under other conditions, such as a more general sample that includes poorly performing firms, or with measures of advertising scaled for firm size (to remove the confounding effect of firm size)? Will the negative relationship between advertising and systematic risk hold when other accounting characteristics that have been shown to link to a firm's systematic risk, which may vary across portfolios, are controlled for (but were not controlled for in Madden, Fehle, and Fournier's study)? In addition, there is a research opportunity to incorporate unobserved firm heterogeneity (to rule out endogeneity caused by omitted variables) and to use lagged predictor variables (to rule out reverse causality), issues that have not been examined in prior research. There is also evidence in the literature that links a firm's R&D expenditure to its financial performance (Boulding and Staelin 1995; Capon, Farley, and Hoenig 1990; Erickson and Jacobson 1992) and shareholder value (Jaffe 1986). We hypothesize that as in the case of advertising, R&D creates intangible market-based assets that insulate the firm from the negative impact of stock market downturns, thus lowering the firm's systematic risk.

Accordingly, we examine the impact of a firm's advertising and R&D on its systematic risk, proposing that a firm's advertising and R&D lower its systematic risk. We test the hypotheses using data on publicly listed firms that we obtained from the COMPUSTAT and Center for Research on Stock Prices (CRSP) databases for the period between 1979 and 2001, which resulted in the creation of a panel data set of 19 five-year moving windows with 3198 observations for 644 firms. Following precedent in the finance literature (Damodaran 2001), we estimate the firm's systematic risk using 60 months of stock returns in a five-year moving window and equal-weighted stock market returns. To eliminate the potentially confounding effects of firm size on systematic risk, we scale the firm's advertising and R&D expenditures by its sales.

We control for the firm's growth, leverage, liquidity, asset size, earnings variability, and dividend payout, factors that finance and accounting scholars have shown to be associated with systematic risk. The model includes two additional control variables that may affect a firm's systematic risk: firm age and competitive intensity in the industry. We estimate the effect of a firm's advertising/sales and R&D/sales on its systematic risk using a fixed-effects model formulation that accounts for unobserved firm heterogeneity and serial correlation of errors.

The results strongly support the hypotheses that higher advertising/sales and higher R&D/sales lower a firm's systematic risk, after we control for factors that prior research has shown to be associated with systematic risk. These two effects are robust to alternative estimates of systematic risk (we estimate β using value-weighted, as opposed to equal-weighted, market returns and relax the restriction that all 60 months of stock returns must be present to estimate β) and to alternative measures of advertising and R&D (we scale them by assets rather than by sales), and the results are not driven by multicollinearity. Our findings are novel and important and hold implications for both marketing theory and practice.

We organize the article as follows: In the next section, we provide a brief overview of systematic risk. We develop hypotheses that relate a firm's advertising and R&D to its systematic risk. We then describe the proposed estimation approach, the data, the measures, and the results. We conclude with a discussion of the study's contributions, its limitations, and opportunities for further research.

An Overview of Systematic Risk

A central issue in portfolio theory in finance is the maximization of returns for people who invest in assets, that is, in firms' stocks (Lintner 1965; Mossin 1966; Sharpe 1964). The key idea of portfolio theory is that investors can construct a portfolio of stocks with imperfectly correlated returns and thus eliminate nonsystematic (i.e., individualistic) risk associated with those stocks. The remaining variability, the firm's systematic risk, reflects the extent to which its stock's return responds to movement of the average return on all stocks in the market.

In 1970, Beaver, Kettler, and Scholes (hereinafter, BKS) related systematic risk to variables that describe the financial position of a firm. Specifically, they suggested that greater systematic risk is related to the following:

- Higher growth because, in a competitive economy, the excessive earnings opportunities may erode when new firms enter the industry;
- Greater leverage because the earnings stream of common shareholders becomes more volatile as debt increases;
- Lower liquidity because liquid or current assets result in less volatile returns than do fixed assets;
- Smaller asset size because smaller firms have greater default risk;
- Lower dividend payout because the need to offer steady dividends causes firms with greater volatility to pay out a lower percentage of earnings;
- Higher levels of earnings variability because this results in a lower payout to stockholders; and
- Higher earnings covariability with the market because this results in higher earnings volatility, again lowering the return on the stocks.

Considering two periods (1947–1956 and 1957–1965), BKS (1970) (1) regressed the aforementioned firm characteristics on systematic risk in the first period and (2) examined whether a model of systematic risk from the first period predicted systematic risk in second period better than did systematic risk in first period.

Two diverse streams of empirical research have emerged from BKS's (1970) study. The first stream of research, which is not related to the current study's objectives, focuses on the prediction of the firm's systematic risk in a future period (Elgers 1980; Eskew 1979; Ismail and Kim 1989). The second stream of research, which is more pertinent to the current study, augments the predictor variables in BKS's study with additional firm characteristics that may explain systematic risk. Although there are several studies in this stream, our review indicates a lack of cumulative knowledge building in this area. Rather, each study adds some new variables to a subset of the variables in BKS's study. Variables considered in prior research include dividend policy (Bildersee 1975), financial structure (Hill and Stone 1980), operating leverage (Mandelker and Rhee 1984), earnings funds flow and cash flow (Ismail and Kim 1989), international diversification (Goldberg and Heflin 1995), and strategic profiles (Veliyath and Ferris 1997).

Similarly, two studies (Bharadwaj and Menon 1993; Kroll, Wright, and Heiens 1999) explore the relationship between aspects of a firm's marketing strategy and its risk. Using service strategic business units from the Profit Impact of Marketing Strategy database, Bharadwaj and Menon (1993) find that some aspects of marketing (e.g., promotional expenditure, sales force expenditure, relative price) are associated with lower variability in return on investment, whereas other aspects of marketing (e.g., advertising, customization) are associated with higher variability in return on investment. Although variability in return on investment, a surrogate for total risk, confounds systematic risk with nonsystematic risk, these results suggest a relationship between firms' marketing activities and their systematic risk. Kroll, Wright, and Heiens (1999) consider a surrogate for systematic risk, the covariance of firms' cash flows relative to a market portfolio of equities, and they find that the superior product quality of strategic business units (again, using the Profit Impact of Marketing Strategy database) decreases the surrogate measure of risk. As we noted previously, Singh, Faircloth, and Nejadmalayeri (2005) and Madden, Fehle, and Fournier (2006) find that higher levels of advertising expenditure are associated with lower systematic risk.

Note that there is a vigorous, ongoing debate about the usefulness of systematic risk for predicting future firm value in the finance literature (Fama and French 1992).[3] However, our focus is on β as a measure of risk, not on β as a predictor of future firm value. To reiterate its central role in investment practice, systematic risk is an important metric for publicly listed firms that measure their stocks' vulnerability to market downturns. Indeed, as testimony of its importance, a review of current investment practices indicates that leading investment firms (e.g., Fidelity, Merrill Lynch, and Value Line) use β extensively in the construction of investment portfolios. Thus, shareholders and senior management of publicly traded firms are interested in β and, consequently, in the impact of advertising and R&D on β.

In summary, although there is much work that relates a firm's accounting characteristics (e.g., dividend payout, growth, leverage, liquidity, asset size, earnings variability) to its systematic risk, much less is known about the relationship between important indicators of marketing strategy (e.g., advertising, R&D expenditures) and systematic risk. Singh, Faircloth, and Nejadmalayeri (2005) and Madden, Fehle, and Fournier (2006) provide two exceptions. To address this research gap, we examine the effects of a firm's advertising and R&D, two important manifestations of the firm's marketing strategy, on its systematic risk.

Theory

We now develop hypotheses that relate a firm's advertising and R&D to its systematic risk. To eliminate the potentially confounding effects of firm size on systematic risk, in the empirical estimation, we scale the firm's advertising and R&D by its sales. We first discuss the effects of the firm's advertising on its systematic risk and then discuss the effects of R&D on systematic risk.

Advertising

A large body of work indicates that advertising has a direct effect on various firm performance metrics, including sales (Leone 1995), profit (Erickson and Jacobson 1992), and firm value (Joshi and Hanssens 2004). Reinforcing these performance rewards to advertising, developments in brand equity (Aaker 1996; Keller 1998) suggest that firms' advertising efforts create consumer and distributor brand equity, an intangible market-based asset with important strategic and performance implications. For example, increased advertising and the resultant brand equity increase the differentiation of a firm's products (Kirmani and Zeithaml 1993) and make them less easily substitutable (Mela, Gupta, and Lehmann 1997). Increased brand equity also increases price premiums (Ailawadi, Neslin, and Lehmann 2003) and lowers price sensitivities (Kaul and Wittink 1995; Sethuraman and Tellis 1991). Furthermore, increased advertising and the resultant higher brand equity produce an asymmetric sales response to sales promotions (Blattberg, Briesch, and Fox 1995), such that highly advertised brands are affected less (than less advertised brands) by competitors' sales promotions.

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[3] Using historical data, Fama and French (1992) examine whether expected returns are better predicted by the firm's previous βs than by other variables. Using realized average returns, they find a stronger empirical correlation of future firm value with a firm's book-to-price and size but not with the measure of its historic βs.

In addition to the benefits of advertising and brand equity in current product markets, advertising and the resultant brand equity also strengthen and stabilize the firm's performance in new product markets. For example, the brand equity of current flagship brands generates greater receptiveness of consumers and distribution channel partners to new product introductions (Kaufman, Jayachandran, and Rose 2006) and enables the firm to migrate customers to more profitable products and/or to cross-sell products to existing customers (Kamakura et al. 2003). Thus, as Srivastava, Shervani, and Fahey (1998) suggest, brand equity can function as financial hedging contracts when firms enter new markets with new technologies. In addition, brand equity also creates both consumer and distributor loyalty, acts as a barrier to competition, and provides bargaining power over distributors; these are all benefits that insulate a firm's stock from market downturns and thus lower its systematic risk (Veliyath and Ferris 1997).

Finally, a firm's brand equity may lower its systematic risk by serving as a capital market information channel to the firm's stockholders (Frieder and Subrahmanyam 2005; Grullon, Kanatas, and Weston 2004). Grullon, Kanatas, and Weston (2004) report that firms with higher advertising have higher liquidity and greater breadth of stock ownership. Frieder and Subrahmanyam (2005) report that a firm's increased brand perceptions (consistent with higher brand equity, as we discussed previously), a direct outcome of its increased advertising, increases ownership of the firm's stock by individual investors (relative to institutional investors) because of individual investors' preferences for stocks with higher-quality information (advertising plays an information role for a firm's stockholders). This higher liquidity and increased breadth of ownership may help insulate the firm's stock returns from market downturns, thus lowering its systematic risk. Thus:

> H_1: The higher a firm's advertising, the lower is its systematic risk.

R&D

There is a large body of finance, management, and marketing research that relates the intangible assets created by R&D to the firm's financial performance. Although there is a debate about the sizes of the effects of R&D investments on different performance metrics (Boulding and Staelin 1995; Erickson and Jacobson 1992), it is well established that firms' R&D investments generate persistent profits (Roberts 2001), high stock returns (Chan, Lakonishok, and Sougiannis 2001; Mizik and Jacobson 2003; Pakes 1985), and superior market value (Jaffe 1986). In a meta-analysis of 210 profitability studies, Capon, Farley, and Hoenig (1990, p. 1157) conclude, "Dollars spent on R&D have an especially strong relationship to increased profitability."

As with advertising-created market-based assets, R&D-created market-based assets may also insulate a firm's stock from market downturns. Veliyath and Ferris (1997) report a relationship between the strategic profile of a firm, including its advertising- and R&D-driven differentiation, and its systematic risk. Similarly, the number of a firm's new product introductions lowers its systematic risk (Chaney, Devinney, and Winer 1991). This relationship between R&D and systematic risk occurs because a firm that invests in R&D exhibits greater dynamic efficiency and greater flexibility than its competitors (which invest less in R&D), enabling it to adapt to environmental changes, including in input prices, technologies, and customers (Miller and Bromiley 1990). This efficiency and flexibility help insulate the firm from market downturns, thus lowering its systematic risk.

We focus on the effects of a firm's R&D, an activity with uncertain returns, on its systematic risk: If the focus is on total risk (nonsystematic risk and systematic risk), R&D may increase total risk because R&D may decrease the predictability of a firm's future income streams (Kothari, Laguerre, and Leone 2002). Analysts exhibit greater disagreement about year-ahead earnings for R&D-intensive firms than for other firms (Barth, Kasznik, and McNichols 2001). Another study notes that postinvestment reported earnings are more highly variable for firms with higher R&D levels than for firms with lower R&D levels (Chambers, Jennings, and Thompson 2002). To the extent that these kinds of volatility are specific to a firm or an industry, they are nonsystematic and can be diversified away (Lubatkin and O'Neill 1987).

In summary, although extant empirical research suggests that R&D can increase a firm's nonsystematic risk, this literature also suggests that R&D creates strategic differentiation, efficiency, and flexibility, which insulate the firm from market downturns, thus lowering its systematic risk. Thus:

> H_2: The higher a firm's R&D, the lower is its systematic risk.

Method

Data

The data for this study included all firms listed on the New York Stock Exchange (NYSE) during the period between 1979 and 2001. We obtained accounting, financial, advertising, and R&D data on firms from COMPUSTAT, and we obtained their stock prices for the computation of systematic risk from CRSP.

Measures

The dependent variable, systematic risk, is an inherently long-term construct that captures the extent to which a firm's stock return covaries with market return (BKS 1970). A firm's systematic risk changes slowly over time. We followed the precedent in prior finance research (Damodaran

2001) and estimated the firm's systematic risk using a five-year moving window; we accomplished this by using stock returns for the previous 60 months, relative to the equal-weighted return for the stock market for that period. We subsequently tested the robustness of the results to β estimates relative to the value-weighted returns and for β estimates when monthly stock returns were available for at least 50 of the 60 months of the moving window (which enables us to increase the number of firms in the data set). In addition, to avoid problems associated with low-priced stocks, we excluded a stock from the five-year moving window if the average of its monthly closing stock prices was less than $2 (Ball, Kothari, and Shanken 1995; Hertzel et al. 2002). Finally, we included a firm in the moving window only if it reported information on its advertising and R&D in COMPUSTAT for all years in the five-year moving window.

Systematic risk. Similar to BKS's (1970) approach, we use monthly stock data to compute firm i's systematic risk measure β_i(hat), *ex post,* for a period by using a least squares regression of the form:

$$(1) \qquad R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, t = \text{Start}, \ldots, \text{End},$$

where $R_{it} = \text{Ln}(D_{it} + P_{it})/P'_{it-1}$ and $R_{mt} = \text{Ln}(L_t/L_{t-1})$, where R_{it} is the *ex post* rate of return for stock i during period t; R_{mt} is an index of the *ex post* return for all NYSE firms during month t (i.e., the market rate of return); α_i is the intercept of the fitted line of R_{it} using R_{mt}; D_{it} is the cash dividend payable on common stock i in month t; P_{it} is the closing price of common stock i at the end of month t; P'_{it-1} is the closing price at the end of month t – 1 adjusted for capital changes (e.g., stock splits, stock dividends); and L_t and L_{t-1} are the Fisher's link relative, a market price index of all firms on the NYSE at months t and t – 1, respectively, adjusted for dividends and all capital changes. The slope of the regression equation β_i(hat) is the empirical estimate of systematic risk β_i of firm i.

We obtained β_i(hat) by estimating a separate regression using the monthly stock returns for each firm i for each five-year moving window, resulting in up to 19 observations per firm. For the first moving window, we used the monthly stock returns for all firms on CRSP for 1979, 1980, 1981, 1982, and 1983 to compute the firm's systematic risk. For the second moving window, we used the monthly stock returns for firms for 1980, 1981, 1982, 1983, and 1984. For the final moving window, we used the monthly stock returns for all firms for 1997, 1998, 1999, 2000, and 2001. To ease interpretation of the results, we eliminated 52 observations in which the firm's estimated systematic risk was negative.

Advertising and R&D. We measured advertising by the mean of the firm's advertising expenditure, as reported in DATA45 and scaled by its sales reported in DATA12, for the five-year period from the annual data reported in COMPUSTAT. DATA45 in COMPUSTAT includes the cost of advertising media (radio, television, newspapers, and periodicals) and promotional expenses.[4] We measured R&D by the mean of the firm's R&D expenditure, as reported in DATA46 and scaled by its sales reported in DATA12, for the five-year period from the annual data reported in COMPUSTAT. Scaling the firm's advertising and R&D expenditures by its sales rules out the alternative explanation that the negative effect of advertising and R&D on systematic risk may be due to larger firms having lower systematic risk. We subsequently test the model and report that estimation results are robust to scaling of the advertising and R&D by the firm's assets (DATA6) instead of its sales.

Given the theoretical processes discussed in the hypotheses development, we anticipate a lagged effect of a firm's advertising and R&D on its systematic risk. Thus, we used lagged measures of advertising/sales and R&D/sales, which preclude a potential reverse-causality explanation of the effects (Boulding and Staelin 1995).

Accounting variables. Given this study's objective of exploring the effects of a firm's advertising and R&D on its systematic risk, as accounting researchers have done, we use accounting variables that BKS (1970) use as control variables in our model. Accordingly, we included six accounting characteristics of the firm in the model: asset growth rate, leverage, liquidity, asset size (log), earnings variability, and dividend payout (for the logic for the operationalization of these variables, see BKS 1970, p. 666). The inclusion of the firm's asset size serves as a further control for the effects of the firm's size on its systematic risk. We are unable to include covariability of earnings, which BKS include in their model, because its calculation requires ten years of data. We provide the definitions of these measures and the data fields from COMPUSTAT used for BKS's computation in the Appendix.

Additional control variables. We also included two additional control variables in the model. First, we included the firm's age, which we measured by the number of years since its listing on the stock market, because older firms may have lower systematic risk. Second, to control for industry-specific effects, following the suggestion of an anonymous reviewer, we included the industry's competitive intensity, which we measured with Herfindahl's four-firm concentration ratio as the proportion of market shares of the largest four firms to the industry's sales at the two-digit Standard Industrial Classification level. A priori, we do not hypothesize the directional effect of competitive intensity. The fixed-effects formulation we employ to estimate the model precludes the inclusion of time-invariant industry dummies in the model.

A total of 3198 observations (for 644 firms) had complete data on systematic risk, lagged advertising/sales, lagged R&D/sales, and the control variables. The number of firms in the sample by each moving window suggests that, over time, the number of firms in each moving window increases at first, reaches a maximum (N = 371 in Window 10 [years = 1989–1993]), and then declines to 162 in the last moving window (years = 1997–2001). This drop in the number of firms in the moving windows over time occurred because of missing data for advertising and R&D. The average value for systematic risk for all firms in a given window varies across the years, ranging from .856 (Window 14) to 1.140 (Window 18), whereas average asset size (log) ranges from $6.243 million (Window 14) to $4.951 million (Window 6). Lagged advertising/sales and lagged R&D/sales vary as follows: for average lagged advertising, highest = .055 in Window 15 to lowest = .033 in Window 1; for average lagged R&D, highest = .088 in Window 15 to lowest = .036 in Window 1. Of the observations, 3% reported zero advertising expenditure, and 3.9% reported zero R&D expenditure. Table 1 contains the descriptive statistics and correlation matrix of the measures, and Figure 1 contains the frequency distribution of asset size (log) and systematic risk of observations in the study.

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[4] Prior research has shown that sales promotion activities negatively affect brand loyalty (Mela, Gupta, and Lehmann 1997) and have a nil effect on stock returns (Pauwels et al. 2004). We are aware that some firms may report sales promotion expenditure as a part of their advertising expenditure. However, because firms do not indicate the split between advertising and sales promotions, we assume that most advertising expenditures reported in DATA45 in COMPUSTAT are related to communication of product benefits to customers. Thus, differences in the percentage of such misreported advertising expenditure that pertains to sales promotion add error to our estimates, making our tests of hypotheses conservative.

A perusal of Table 1 and Table 2 (which we discuss in detail subsequently) suggests that the pattern of bivariate correlation matrix in Table 1 is different from the pattern of regression results in Table 2. For example, the model estimation results in Table 2 indicate that advertising/sales and R&D/sales have coefficients that are negative and significant at $p < .01$. However, in the bivariate correlation matrix in Table 1, the correlation between R&D/sales and β is positive and significant at $p < .01$, and the correlation between advertising/sales and β is negative and significant only at $p < .10$. This "disconnect" occurs because the bivariate correlation matrix does not account for the fixed effects, serial correlation, or window dummies in our model structure. To explore this issue further, we created an "adjusted" bivariate correlation matrix, in which we removed the effects of fixed effects, serial correlation, and window dummies from the predictor variables by regressing fixed effects, serial correlation, and window dummies on each of the predictor variables and systematic risk. We used the residuals from each of these regressions to create an adjusted correlation matrix (this and all other results that we do not report herein are available on request). The pattern of correlations in the adjusted correlation matrix corresponds closely to the regression results in Table 2.[5] Thus, multicollinearity does not appear to be driving the results of the model estimation.

Results

Model Estimation Procedure

Because the panel data set of moving windows consists of repeated observations of firms, we estimated a fixed-effects, cross-sectional, time-series regression model with a correction for serial correlation of errors (Baltagi and Wu 1999; Bhargava, Franzini, and Narendranathan 1982; Woolridge 2002). Specifically, the model has the following structure:

$$(2) \qquad Y_{it} = \alpha + X_{it}\beta + v_i + \varepsilon_{it} = 1, \ldots, N; t = 1, \ldots, T_i;$$

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[5] We also performed stepwise regression analyses, adding one predictor variable at a time to the model, and found consistent results for the effects of lagged advertising and lagged R&D (the directionality, significance, and the sizes of the coefficients) across these stepwise regressions, showing that there are no harmful effects of multicollinearity.

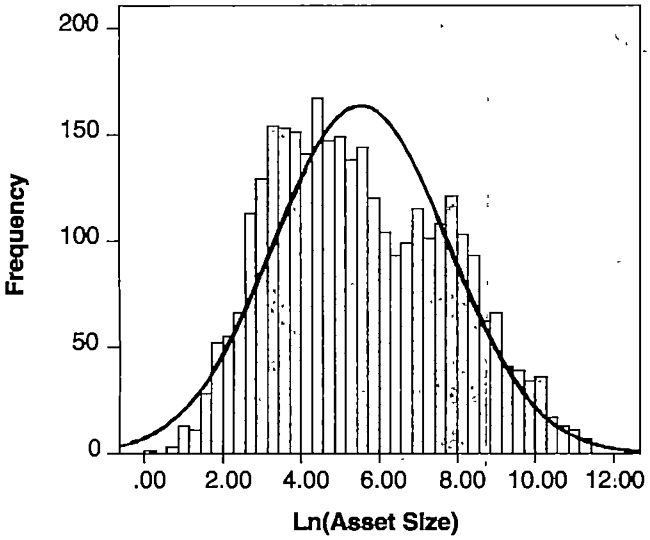
TABLE 1
Descriptive Statistics and Bivariate Correlation Matrix for Variables In Proposed Model

Variable	M (SD)	1	2	3	4	5	6	7	8	9	10
1. Systematic risk	1.042 (.527)	1.000									
2. Lagged advertising/sales	.040 (.053)	–.051	1.000								
3. Lagged R&D/sales	.068 (.120)	.228	.155	1.000							
4. Growth	.081 (.112)	.147	–.019	.002	1.000						
5. Leverage	.410 (.237)	.058	.068	–.036	–.121	1.000					
6. Liquidity	3.153 (2.989)	.104	.083	.380	.056	–.369	1.000				
7. Asset size	5.167 (2.221)	–.389	.046	–.164	–.009	.105	.340	1.000			
8. Earnings variability	.077 (.159)	.220	.005	.054	–.250	.181	–.052	–.174	1.000		
9. Dividend payout	.388 (.853)	–.024	–.004	.003	–.025	.002	–.012	.028	.005	1.000	
10. Age	19.152 (.112)	–.392	.079	–.189	–.154	.107	–.243	–.105	–.128	.022	1.000
11. Competitive intensity	.399 (.112)	.065	–.182	–.076	–.047	.009	–.016	.629	.060	–.004	–.071

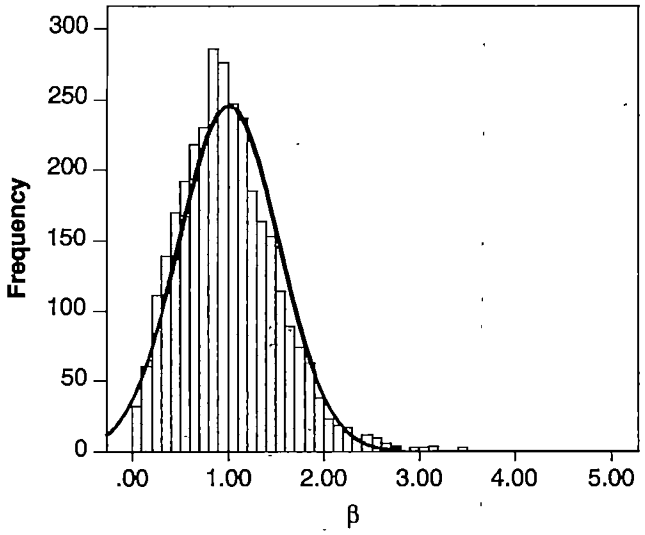
Notes: All correlations greater than .220 are significant at $p < .01$, all correlations greater than .11 are significant at $p < .05$, and all correlations greater than .023 are significant at $p <$ 10 where $\varepsilon_{it} = \rho\varepsilon_{it-1} + \eta_{it}$ ($|\rho| < 1$, and η_{it} is independent and identically distributed [i.i.d.] with mean 0 and variance σ^2_{η}) and v_i are assumed to be fixed parameters that may be correlated with the covariates X_{it}. The X_{it} include the accounting variables of growth, leverage, liquidity, asset size, earnings variability, dividend payout, age, competitive intensity, and advertising and R&D. The failure to correct for serial correlation of errors, if it is present, can result in inflated standard errors of parameter estimates and incorrect tests of hypotheses (for the detailed statistics of the fixed-effects panel data model with correction for first-order serial correlation of errors, see Bhargava, Franzini, and Narendranathan 1982).[6]

Figure 1
Frequency Distribution

A: Firm Size



B: Systematic Risk (β)



Notes: For Panel A, M (SD) = 5.167 (2.221), and for Panel B, M (SD) = 1.042 (.527).

We estimated the model using the "xtregar" procedure in STATA 9.0. In addition to the predictor variables of lagged advertising/sales and lagged R&D/sales, we also included BKS's (1970) control variables and the two additional control variables of age and competitive intensity. As discussed previously, we used lagged measures of advertising/sales and R&D/sales. Because this structure precludes a potential reverse-causality explanation, we can explore a causal relationship between advertising/sales and systematic risk and between R&D/sales and systematic risk (Boulding and Staelin 1995). We included dummies for each moving window to account for any differences across windows.

We checked for first-order serial correlation in errors, as Woolridge (2002) proposes. This test rejected the hypothesis that there is no first-order serial correlation ($p < .01$), in support of the inclusion of an autoregressive (AR1) disturbance term. We report the results of the estimation of the proposed model in Column 1 of Table 2.

The proposed model is statistically significant (F(671, 2527) = 17.90, $p < .01$), and the R-square (within) for the proposed model is .161. The rejection of the hypothesis of null fixed effects (F-value is significant at $p < .01$) reinforces the need for fixed-effects correction. The estimated autocorrelation coefficient, ρ, is large at .668, and the Durbin–Watson statistic (Baltagi and Wu 1999) is not significant (t = 1.200, n.s.), reconfirming the need to adjust for serial correlation in errors.

We first compare the coefficients of the accounting variables in this study with BKS's (1970) results. We note that BKS report significant effects for dividend payout (b = –.58, $p < .01$), growth (b = .84, $p < .05$), and earnings variability (b = 3.03, $p < .01$). In our results, significant coefficients indicated that growth (b = .359, $p < .01$) and leverage (b = .515, $p < .01$) are positively associated with a firm's systematic risk, whereas asset size (b = –.091, $p < .01$) is negatively associated with systematic risk. Given the changes in stock market regimes over time and the refinements in the estimation procedure we use herein (i.e., we use a panel data model, incorporating fixed effects and serial correlation in errors), the differences in this study's coefficients relative to those that BKS report are not surprising.[7]

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[6] The most frequently analyzed process in the empirical econometrics literature is the first-order autoregression, or AR(1), process in which the errors across time t and t – 1 are correlated. Higher-order processes involving several periods are both intractable and place a high burden on the researchers to justify more complex time-series processes. Thus, as Greene (2003, p. 257) notes, "the first-order autoregression has withstood the test of time and experimentation as a reasonable model for underlying processes that probably, in truth, are impenetrably complex."

[7] We also estimated the model that BKS (1970) estimate for the 20 years in this study by constructing two data sets—one for the period 1980–1989 and one for the period 1990–1999—by averaging the various accounting variables for the 10 years following the procedure in BKS's article. The results of the ordinary least squares regression for the model with accounting variables were significant in both 10-year periods: Period 1: F(6, 338) = 22.501, $p < .01$; Period 2: F(6, 231) = 17.742, $p < .01$. The R-squares are

TABLE 2
Advertising, R&D, and Systematic Risk: Estimation Results

Variable	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Minimum number of returns observations for estimating β	60	60	50	50	60	60
Market return used in estimating β	Equal weighted	Value weighted	Equal weighted	Value weighted	Equal weighted	Equal weighted
Model specification	Levels of variables	Levels of variables	Levels of variables	Levels of variables	Changes in variables	Changes in variables[a]
Intercept	–.542 (.037)***	–.221 (.039)***	–.598 (.038)***	–.278 (.041)***	–.034 (.045)	.025 (.014)*
Lagged advertising/sales	–3.187 (.754)***	–2.282 (.785)***	–3.419 (.705)***	–1.845 (.732)***	–2.608 (.584)***	–.022 (.004)***
Lagged R&D/sales	–.501 (.180)***	–.989 (.190)***	–.467 (.175)***	–1.000 (.183)***	–.202 (.118)*	–.009 (.004)**
Growth	.359 (.084)***	.403 (.089)**	.339 (.081)***	.379 (.085)**	.443 (.073)***	.026 (.004)***
Leverage	.515 (.124)***	.006 (.129)	.474 (.115)***	–.065 (.119)	.459 (.090)***	.021 (.004)***
Liquidity	.001 (.010)	.002 (.011)	.001 (.010)	.001 (.010)	.005 (.007)	.001 (.004)
Asset size	–.091 (.032)***	–.093 (.033)***	–.107 (.031)***	–.092 (.032)***	–.014 (.031)	–.001 (.004)
Earnings variability	–.018 (.032)	–.059 (.034)*	–.081 (.028)	–.018 (.029)	–.036 (.032)	–.004 (.004)
Dividend payout	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	–.001 (.004)
Age	–.022 (.006)***	.021 (.007)**	–.021 (.006)***	–.023 (.007)***	—	—
Competitive intensity	–.885 (.335)***	–.598 (.346)*	–.830 (.327)***	–.065 (.338)*	–.530 (.331)	–.008 (.005)
Serial correlation (ρ)	.668	.656	.654	.643	—	—
R^2	.161	.106	.155	.102	.052	.052
Number of firms (observations)	644 (3198)	644 (3198)	711 (3457)	711 (3457)	644 (3198)	644 (3198)
F (d.f.)	17.901 (671, 2527)	11.051 (671, 2527)	18.472 (738, 2719)	11.421 (738, 2719)	6.910 (25, 3172)	6.910 (25, 3172)

*$p < .10$
**$p < .05$.
***$p < .01$.
[a] We used factor-scored predictor variables for this model.
Notes: Coefficient (standard errors) are in the columns. The models also include window dummies, some of which are significant at $p < .01$.

We infer that differences among our findings, those in BKS's study, and those of BKS's model approach with the 1980–1999 data (see n. 6) arise because of differences (1) in stock market regimes across the years that result from changes in the range of predictor variables and (2) in the econometric estimation procedure between our study and BKS's study—we incorporate information on the panel data structure in the estimation, whereas BKS do not.

With respect to the other control variables, the firm's age (b = –.022, $p < .01$) and competitive intensity (b = –.885, $p < .01$) are significantly associated with lower systematic risk. The accounting variables of liquidity (b = .001, n.s.), earnings variability (b = –.018, n.s.), and dividend payout (b = .000, n.s.) are not related to systematic risk.

We next discuss the two hypothesized effects. The results indicate that as H_1 and H_2 predicted, respectively, higher lagged advertising/sales (b = –3.187, $p < .01$) and higher lagged R&D/sales (b = –.501, $p < .01$) lower the firm's systematic risk. Following an anonymous reviewer's suggestion, we reestimated the proposed model, including the square of lagged advertising/sales and the square of lagged R&D/sales, to explore nonlinear effects. The results were similar to those we report in Column 1 of Table 2, with no significant effect for the squared terms. We discuss this finding in detail in the "Discussion" section. We also reestimated the model using the interaction effect of lagged advertising and lagged R&D, but we find no support for this interaction effect. Thus, the estimation results strongly support H_1 and H_2, indicating that after we control for factors that accounting researchers have shown to affect the firm's systematic risk, increases in both advertising/sales and R&D/sales lower a firm's systematic risk.

Additional Analyses

Explanatory power of proposed model. We compared the performance of the proposed model, which includes lagged advertising/sales and lagged R&D/sales, with a baseline model that includes only the accounting measures of growth, leverage, liquidity, asset size, dividend payout, and earnings variability and the two additional control variables of age and competitive intensity (we do not report the results here). The model with lagged advertising/sales and lagged R&D/sales outperforms the baseline model on the basis of the Schwarz Bayesian information criterion (a lower number indicates superior fit): The proposed model = 3705.873, and the baseline model = 3741.607. The direction and significance levels of the coefficients of BKS's (1970) variables in this baseline model without lagged advertising/sales and lagged R&D/sales are unchanged, again confirming that there is no evidence of multicollinearity of lagged advertising/sales and lagged R&D/sales with the control variables.

Alternative estimates of systematic risk. The proposed model we report in Column 1 of Table 2 uses equal-weighted market returns to estimate the firm's systematic risk. To examine the robustness of the proposed model's results to alternative specifications for systematic risk, we also estimated β for the five-year moving window using the value-weighted market return, and in general, we obtain consistent results for the effects of advertising/sales and R&D/sales on the firm's systematic risk with value-weighted β estimates (see Column 2 of Table 2).

To examine the robustness of the negative effects of advertising/sales and R&D/sales on β, we expanded the data to include firms for which only 50 of the 60 months of stock returns in a moving window were available for β estimation. Columns 3 and 4 of Table 2 contain the results of model estimation using equal-weighted and value-weighted measures of market return in the β estimation for the expanded sample, which includes observations with 50 or more months of stock returns for the 60-month moving window. The effects of advertising/sales and R&D/sales on systematic risk using the larger data set of firms with as few as 50 months of stock returns are similar to those we obtained using the smaller data set, which includes firms for which all 60 months of stock returns were available to estimate β.

Changes regression. Following an anonymous reviewer's suggestion, we explored the robustness of the results using a changes regression (Boulding and Staelin 1995). We created the difference value for a variable as the difference between the variable at time t and at time t – 1. The correlation matrix of the differenced variables suggested potential multicollinearity problems, especially between "change in advertising scaled by sales" and "change in R&D scaled to sales," which perhaps is not surprising because increases in R&D are likely to be associated with increases in advertising. To reduce the impact of this multicollinearity, we orthogonalized predictor variables using factor analysis. Varimax rotation ensured that each factor had only one predictor variable that loaded heavily on that factor (variables' loadings on their respective factors exceeded .98). We report the results of the changes regression models using difference scores for β, which we estimated with 60 months of equal-weighted returns using both raw predictor variables and factor-score predictor variables (to adjust for potential multicollinearity in the raw predictor

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as follows: Period 1 = .285, and Period 2 = .315). The following accounting variables were significant: for Period 1, growth (+ and $p < .01$), leverage (+ and $p < .05$), earnings variability (+ and $p < .01$), and asset size (– and $p < .01$); for Period 2, growth (+ and $p < .10$), leverage (+ and $p < .05$), earnings variability (+ and $p < .01$), and asset size (– and $p <$ 01). From these results, we can observe the impact of methodology. With BKS's data and methodology, growth, earnings variability, and dividend payout were significantly associated with β, but asset size and leverage were not associated with β. In terms of why BKS did not identify asset size and leverage as predictors of β, recall that BKS eliminated leverage and asset size in a stepwise regression of data averaged over 10 years. We conjecture that panel-structure-adjusted correlations may have shown that leverage and asset size were (as they are now) good predictors of systematic risk. The raw correlation structure in our panel data is consistent with this conjecture. In the panel data set, correlations of liquidity with both asset size (ρ = .34) and leverage (ρ = –.37) are high. In summary, we suggest that the difference between our results and BKS's results are, in large part, driven by our up-to-date econometric estimation approach. After correcting for methodology, the remaining differences in our findings might be due to change in the marketplace, or they might be because BKS's use of stepwise regression artificially eliminated leverage and asset size that our proposed model (with its panel structure) identifies as important predictors of β.

variables) in Columns 5 and 6 of Table 2. The results of this estimation indicate a reasonable model fit and suggest that increases in a firm's lagged advertising/sales and lagged R&D/sales reduce the firm's systematic risk, in support of H_1 and H_2.[8]

Reverse causality. As we noted, the model we estimated considered the impact of the firm's advertising/sales in Period t – 1 and R&D/sales in Period t – 1 on systematic risk in Period t to rule out reverse causation. However, it is possible that either because of inertia (i.e., advertising budgets and R&D budgets are set as a percentage of sales) or because managers are forward looking, advertising and R&D budgets in Period t – 1 may be related to Period t's firm characteristics, particularly, systematic risk.

To rule out reverse causality, we performed the Granger-causality Wald tests (Dekimpe and Hanssens 2000; Granger 1969). Specifically, we performed Granger-causality Wald tests for each time series in the data set using a bivariate approach (Leeflang and Wittink 1992) between (1) the firm's systematic risk and its advertising/sales and (2) the firm's systematic risk and its R&D/sales. The results of the Wald tests indicate that a firm's systematic risk does not "Granger cause" either advertising or R&D, empirically ruling out the reverse-causality explanation.

In addition, we performed two regressions to rule out potential reverse-causality explanations. First, we regressed advertising/sales in Period t as a function of all predictor variables in the proposed model and β in Period t – 1. Second, we regressed R&D/sales in Period t as a function of all predictor variables in the proposed model and β in Period t – 1. Both models included fixed effects, an autocorrelation error term, and window dummies. The results of the regressions (we do not report these here) indicate that consistent with the lack of reverse causality we established previously, β in Period t – 1 does not affect either advertising/sales or R&D/sales in Period t.

Potential endogeneity of advertising and R&D. Following the explanation that a firm's managers may be forward looking, we also attempted to rule out potential endogeneity explanations of the firm's advertising/sales and R&D/sales. First, our fixed-effects formulation rules out endogeneity that might be caused by omitted variables. Second, following the work of Boulding and Staelin (1995), we checked for endogeneity of lagged advertising/sales and lagged R&D/sales using an instrumental variable estimation procedure.

We used the firm's advertising/sales and R&D/sales in Period t – 2 as the instrument for the firm's advertising/sales and R&D/sales in Period t – 1 and reestimated the model that relates a firm's two-period-lagged advertising/sales and R&D/sales to its systematic risk. The results of this instrumental variable estimation procedure (we do not report these here) are consistent with those we obtained with the one-period-lagged predictor variables of advertising/sales and R&D/sales reported for the proposed model in Column 1 of Table 2. Following the instrumental variable estimation, we also performed the Davidson–MacKinnon test (Woolridge 2002; pp. 118–22) of endogeneity for lagged advertising and lagged R&D and found no support for endogeneity of either advertising or R&D.

Alternative measures of advertising and R&D. In the results discussed thus far, we scaled both the firm's advertising and R&D expenditures by its sales. Following an anonymous reviewer's suggestion, we reestimated the model with measures of the firm's advertising and R&D scaled by its assets. The results (we do not report these here) using a model identical to the model reported in Column 1 of Table 2, but with advertising/sales and R&D/sales replaced by the advertising/assets and R&D/assets, respectively, indicate a reasonable model fit (F is significant at $p < .01$). The directionality of the parameter estimates of the predictor variables are consistent with those we report in Column 1 of Table 2, though the significance level changes to $p < .05$; advertising/assets ($b = -.737$, $p < .05$) and R&D/assets ($b = -1.024$, $p < .05$) lower the firm's systematic risk.

Alternative measure of earnings variability. In addition, again following an anonymous reviewer's suggestion, we reestimated the model using cash flow variability as a control variable rather than earnings variability, as BKS (1970) use. Again, the results (we do not report these here) indicate a reasonable model fit (F is significant at $p < .01$); the results are consistent for the effects of both advertising/sales ($b = -3.509$, $p < .01$) and R&D/sales ($b = -.443$, $p < .05$) on systematic risk.

Thus, the results are robust to alternative model specifications, including the regression of differenced variables; alternative measures of systematic risk, including equal-weighted or value-weighted market returns and 60 months or 50 months of returns; alternative measures of advertising and R&D scaled by the firm's sales or assets; and earnings variability or cash flow variability. We also empirically rule out reverse causality (i.e., systematic risk lowers advertising and R&D) and endogeneity of both advertising and R&D expenditures. In summary, the additional analyses strengthen our confidence in our key findings that both lagged advertising/sales and lagged R&D/sales lower a firm's systematic risk.

Discussion

The accountability of marketing initiatives, especially as measured by metrics of interest to a firm's shareholders, is under increasing scrutiny from senior management and finance executives who control marketing budgets. Not surprisingly, marketing scholars have turned their attention to relationships between various aspects of a firm's marketing strategy and shareholder value, producing a wealth of insights that indicate an important role for marketing in shareholder wealth creation. However, there are few insights that relate a firm's marketing initiatives to its systematic risk, an important metric of risk for publicly listed firms. We examine the impact of a firm's advertising and R&D, two important manifestations of a firm's marketing strategy, on its systematic risk.

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[8] In general, we obtain similar results for the models that use β computed with value-weighted market return.

Theoretical Implications

To our knowledge, this is the first empirical study to cover a broad, multi-industry sample of firms over a 22-year period to demonstrate that after accounting and finance factors related to systematic risk are controlled for, increases in advertising/sales and R&D/sales lower a firm's systematic risk. The negative relationship between a firm's advertising expenditure and its systematic risk (shown by Singh, Faircloth, and Nejadmalayeri [2005] in a limited empirical context and by Madden, Fehle, and Fournier [2006], who do not control for accounting and finance factors and firms-specific effects) holds up for all firms across a period that extends from 1979 to 2001. By focusing on the firm's systematic risk, an important metric of considerable interest to senior executives of publicly listed firms, we address the several calls for marketing scholars and practitioners to speak in the language of finance (Rust et al. 2004; Srivastava, Shervani, and Fahey 1998).

The finding of a nonsignificant effect of the quadratic term for a firm's advertising/sales and R&D/sales on its systematic risk is notable and merits discussion. We offer two possible explanations for this phenomenon. First, perhaps there are diminishing returns to increased advertising/sales (and R&D/sales) for some range of advertising/sales (and R&D/sales) values, and perhaps advertising/sales (and R&D/sales) values have been constrained well below that optimum level, such that the relationship is linear. Such a situation may occur if firms are wise enough to set advertising/sales (and R&D/sales) for optimal financial returns and if the optimal financial return level is lower than that required to deliver the lowest β. Alternatively, the linear effect of advertising/sales may occur because a firm's senior management and finance executives lack the tools to evaluate the potential impact and thus set advertising/sales below levels that yield the lowest systematic risk. A second possible explanation for our inability to detect a quadratic effect when there are diminishing returns to increases in advertising/sales is heterogeneity across firms, industries, and/or time in the relationship between advertising/sales and β. As finance and accounting researchers have done previously, in the interest of generality, we estimate our model with the broadest possible cross-section of firms and industries and for an extended period, which lends confidence to the study's findings. Further research that explores firm, industry, and/or time-specific effects that moderate the effects of advertising on a firm's systematic risk may uncover firms, industries, or periods for which such diminishing returns may be identifiable.

In a departure from most prior studies of systematic risk that have used a silo-based approach (i.e., used only accounting and financial measures), we include accounting, financial, and marketing variables (in this case, advertising and R&D) in our model of systematic risk. The negative impact of advertising/sales and R&D/sales on systematic risk in our model, which also includes financial variables, suggests the potential interchangeability between a firm's marketing and financial choice variables in managing systematic risk. Further research that examines other interchangeable effects of other aspects of firms' marketing and financial strategies on metrics of interest to capital markets (e.g., cost of capital, intangible value, stock returns) would be valuable to senior marketing executives, who are often under pressure from senior management teams to justify investments in advertising and R&D programs.

This study's finding that a firm's advertising/sales and R&D/sales lowers its systematic risk, combined with results from other studies (Madden, Fehle, and Fournier 2006; Mizik and Jacobson 2003) that show that a firm's advertising increases its stock return, leads to an interesting conjecture. Consistent with the notion that advertising and R&D increase a firm's stock returns, a post hoc analysis indicated that lagged advertising/sales and lagged R&D/sales were highly correlated with the firm's intangible value (ρ[advertising/sales, Tobin's q] = .013, $p < .01$; ρ[(R&D/sales, Tobin's q] = .283, $p < .01$). Specifically, we conjecture that the risk-lowering and return-enhancing effects of advertising and R&D may contribute to the anomaly that Fama and French (1992) identify. Although the capital asset pricing model assumes that firms with greater systematic risk can expect higher future returns, Fama and French find that there is no relationship between a firm's risk in one period and its return in the future. If firms that invest in advertising and R&D are able to raise their returns while lowering their risk, it might be expected that there would be no empirical evidence of the high risk–high return link. Such an effect would be consistent with the finding in the finance literature that investors prefer highly advertised firms (Grullon, Kanatas, and Weston 2004) and the finding in the marketing literature that advertising has a direct impact on stock price beyond its indirect effect through increased sales (Joshi and Hanssens 2004). Empirical research that explores this issue further would be valuable and would contribute to both the marketing and the finance literature.

Managerial Implications

The study's findings also generate useful implications for managerial practice. Given the increasing calls for the accountability of marketing initiatives, our findings that a firm's higher advertising/sales and R&D/sales lower its systematic risk are novel and useful. Marketing executives can use these findings to stress the multifaceted role of strong advertising and R&D programs, beyond their effects on market (e.g., sales, market shares) and financial (e.g., return on assets, cash flow) performance outcomes.

Given the dual benefits of advertising and R&D for firm value through effects on both stock returns (Mizik and Jacobson 2003) and systematic risk, firms must be cautious in cutting back on their advertising and R&D programs. A reduction in a firm's advertising or R&D can have a double negative effect, not only reducing its financial performance, attendant cash flows, and stock returns but also increasing its systematic risk, cost of capital, and discount rate.

We believe that the study's findings may surprise senior management and finance executives, some of whom may view their firms' advertising and R&D programs as discretionary activities. Indeed, we believe that marketing executives can raise potentially provocative questions about whether extant allocation norms for advertising and R&D (e.g., as a fixed percentage of sales) still apply. Could marketing executives rightfully argue that some proportion of the firm's advertising and R&D budgets be considered a financial expenditure aimed at lowering its interest burden?

Although we are mindful about this study's limited influence in changing finance managers' mind-sets about the uncertain returns to their firms' advertising and R&D investments, we hope that it serves as an impetus for an ongoing dialogue among senior management, finance executives, and marketing executives about the important "financial" role of their firms' advertising and R&D expenditures (Rust et al. 2004).

Indeed, the study's specific findings can guide marketing executives to initiate a dialogue with their finance counterparts. For example, what are the firm's historical levels of advertising/sales, R&D/sales, and systematic risk, both independently and compared with those of other firms in the industry? What are the implications of advertising and R&D budgets going forward not only for the firm's marketing objectives (e.g., sales, market share) and financial objectives (e.g., cash flows, return on assets) but also for its systematic risk? We anticipate that the answers to these and related questions could guide the development of benchmarks to assess the returns to advertising and R&D programs. Such ongoing dialogue may be instructive to senior management and finance executives who control advertising and R&D budgets but are skeptical about the financial accountability of returns to these investments.

Limitations and Further Research

Given data availability constraints for publicly listed firms, we focused on the relationship between a firm's systematic risk and its advertising and R&D, two important indicators of the firm's emphasis on differentiation and, therefore, of its marketing strategy. Theoretical research using complementary methods (e.g., in-depth interviews, surveys, field studies) to develop a conceptual model and propositional inventories that relate other elements of marketing strategy (e.g., marketing channels) to systematic risk will be useful in setting a research agenda for further empirical research.

Furthermore, we measured the firm's advertising and R&D using aggregated, annual dollar amounts scaled by the firm's sales. Although advertising and R&D expenditures are important, especially from the perspective of senior management and finance executives, they represent consolidated input measures, which do not account for differences in implementation of advertising (e.g., creativity of advertising campaigns, efficiency of media planning) and new product development programs (e.g., intellectual property rights, new product success rates, entry timing). Disaggregated measures of a firm's advertising and R&D programs for all publicly listed firms are not available. Further research that focuses on a few industry contexts and uses disaggregated measures of the various elements of advertising programs and new product development programs, including aspects of the programs' effectiveness, could provide a useful extension to generate actionable managerial implications regarding the effects of various elements of a firm's advertising and new product development program on its systematic risk.

In summary, we view this study as an important first step in establishing that advertising and R&D lower systematic risk of a firm's stock. We hope that the study's findings stimulate further work in this area.

APPENDIX
Proposed Model Predictor Variable Definitions and Measures

Variable	Definition	Measure
Advertising/sales	The five-year moving average of advertising/sales.	(1/5) × Σ Data45/Data12 for five years
R&D/sales	The five-year moving average of R&D/sales	(1/5) × Σ Data46/Data12 for 5 years
Dividend payout	The five-year moving average of cash dividends/earnings	(1/5) × Σ Cash dividend/Available income for five years
Growth	The five-year moving average of terminal total assets/initial assets	(1/5) × Ln(Total assets$_5$/Total assets$_1$)
Leverage	The five-year moving average of total senior securities (preferred stocks and bonds)/total assets	(1/5) × Σ Total senior securities/Total assets for five years
Liquidity	The five-year moving average of current ratio	(1/5) × Σ Current assets/Current liabilities for five years
Asset size	The five-year moving average of total assets	(1/5) × Σ Ln(Total assets) for five years
Variability of earnings	The five-year moving average of standard deviation of earnings:price ratio	$(\Sigma[E_t/P_{t-1} - E\{E_t/P_{t-1}\}]^2/4)^{1/2}$ for period t = 2 to t = 5, where P_t and E_t are the market value of common stocks and earnings at time t, respectively

APPENDIX
Continued

Variable	Definition	Measure
Firm age	Number of years since the stock's first listing on the stock market	—
Competitive intensity	The four-firm Herfindahl's concentration index	Proportion of market share of the top four firms in the industry defined by two digits of the Standard Industrial Classification code.

Notes: We define the measures for the various predictor variables for each firm i for each of the 19 five-year moving windows. All the variables have a subscript i for each firm.

COMPUSTAT Data Items Used in Constructing Variables

Name of Variable Component	COMPUSTAT Annual Data Items
Advertising/sales	DATA45/DATA12
R&D/sales	DATA46/DATA12
Total assets	DATA6
Income available for common stockholders	DATA20
Market value of common stock (P_t)	DATA24 × DATA25 × 1000
Total senior securities (TotalSecurity)	DATA5 + DATA9 + DATA10
Current asset (CurrentAsset)	DATA4
Current liabilities (CurrentLiability)	DATA5
Cash dividends (CashDividend)	DATA21
Herfindahl's concentration index	DATA12

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Stephen J. Carson

When to Give Up Control of Outsourced New Product Development

The author investigates the impact of client control on supplier task performance in the burgeoning area of outsourced new product development. In relationships in which the outsourced task requires a high degree of creativity on the part of the supplier, *ex ante* contractual control is shown to increase supplier performance. In contrast, *ex post* client control is shown to reduce supplier performance, though certain highly skilled clients can overcome this effect. Behaviorally, clients exercise less control both *ex ante* and *ex post* in relationships in which the outsourced task requires a high degree of creativity on the part of the supplier. Managerially, the results suggest that clients should use more *ex ante* control to govern highly creative tasks. In general, clients should use less *ex post* control over such tasks, though highly skilled clients can actually benefit from using greater control.

Until recently, firms conducted virtually all new product development activities in-house. The traditional prominence of internal new product development can be attributed to the strategic importance of innovation to the long-term performance of the firm, a desire to maintain control of core technologies and intellectual property, and the difficulty of coordinating uncertain product development relationships across organizational boundaries.

However new product development processes have changed significantly over the past two decades. Firms increasingly outsource new product development activities to external organizations as part of a process called "rapid distributed innovation" or "open innovation" (Chesbrough 2003). The popularity of outsourcing is due in part to firms' ability to reduce development costs, shorten time to market, improve flexibility, and gain access to the specialized resources of external suppliers. In a short time, outsourcing has dramatically altered new product development in industries such as automobiles, aerospace, computers, telecommunications, pharmaceuticals, chemicals, and software, in which product development has come to be viewed fundamentally as a function dispersed across collaborating firms (Dahan and Hauser 2002; Quinn 2000). Even in less high-technology industries, initiatives such as Procter & Gamble's "Connect and Develop," in which the company aims to source 50% of its new products from outside the company, suggest a trend toward greater outsourcing.

New product development relationships differ from more typical channel relationships (e.g., material supply, distribution) in part because they require an often considerable degree of creativity on the part of external suppliers. Despite the importance afforded to creativity in the general marketing literature (e.g., Andrews and Smith 1996), there has been limited empirical research into how firms should alter their channel governance structures to reflect the creative (or noncreative) nature of the outsourced task. The objective of this article is to examine this issue in the context of outsourced new product development, in which the management of creative work is especially germane.

Firms appear to recognize the fragile nature of creativity and often scale back control of creative tasks when organizing their internal new product development activities. Well-known examples of insulating product development teams from outside control within the firm include General Motor's organization of its Saturn and Hummer divisions and Sun Microsystems's development of its JAVA programming language, all of which occurred largely "outside" the control structure of the parent firm (Miller and Morris 1999). However, there is little evidence of either a descriptive or a prescriptive nature on the control of product development when the work is outsourced. Do firms adapt their relationship governance practices to reflect the level of creativity required by the task? Should they?

To develop theory, this study draws principally on the organizational creativity literature. The general hypothesis that emerges from the creativity literature is that client control is detrimental to supplier task performance in relationships in which the outsourced task requires a high degree of creativity on the part of the supplier (Andrews and Smith 1996; Thompson 1965). Thus, clients would be expected to exercise less control over suppliers to the extent that the outsourced task in the relationship is creative in nature.

The term "creative in nature" means that the task requires the supplier to be creative to perform the work successfully. This is an a priori characteristic of the task that is conceptually distinct from the actual (i.e., a posteriori) creativity that the supplier subsequently exhibits in performing

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the work. That is, a task may be creative in nature—in the sense that it requires the supplier to be creative—but the supplier may exhibit a low level of creativity in its actual performance. The focus herein is on the creative nature of the task as the predictor of governance because the control structure of the relationship is set in place largely *ex ante* when only the nature of the task is observable (Robinson and Stuart 2003). The supplier's actual creativity is assessed as part of the task performance measure, as discussed subsequently.

In the next section, I present the theory and hypothesize a two-stage model in which the client first selects levels of *ex ante* and *ex post* control depending on the creative or noncreative nature of the task, and then the nature of the task and the way it is controlled interact to determine the supplier's task performance. The estimation controls for the effects of self-selection of governance and for common method variance.

Theory and Hypotheses

Data published by the National Science Foundation (2005) and other industry benchmarking studies (Duga and Studt 2005; Roberts 1995) suggest an increase in outsourced development activities over the past two decades, as Figure 1 illustrates. Although hard data on outsourced product development remain somewhat rare, a host of anecdotal and case-study evidence has emerged in industry journals and the general business press that suggests a long-term trend toward greater outsourcing of product development (e.g., Engardio et al. 2005).

This study examines new product development relationships between clients (i.e., outsourcing firms) and suppliers. The suppliers in the data are contract research organizations—that is, independent, for-profit firms that are hired by clients to perform development work, most often on a time-and-effort or cost-plus basis. Typically, the supplier develops a particular technology for use in the client's product, though occasionally the supplier delivers a complete "turnkey" new product. In all cases, the work is financially sponsored by the client. Thus, the data do not include collaborative development relationships between equally placed partners (e.g., alliances, joint ventures) or simple marketing arrangements in which suppliers independently develop new products and subsequently bring them to market with the aid of the client organization. Furthermore, to isolate the unique governance requirements associated with product development rather than multifaceted manufacturing relationships, cases in which contract manufacturers are asked to perform new product development are excluded.

Control, Creativity, and Task Performance

As alluded to previously, product development relationships often require significant creativity on the part of the supplier. Indeed, many tasks are outsourced specifically to tap the superior skills of external suppliers and increase the likelihood of creative outcomes. Creativity is a delicate process and is vulnerable to numerous distortions if it is governed inappropriately, particularly if it is overcontrolled. Thus, clients must carefully consider the impact of their control on supplier task performance.

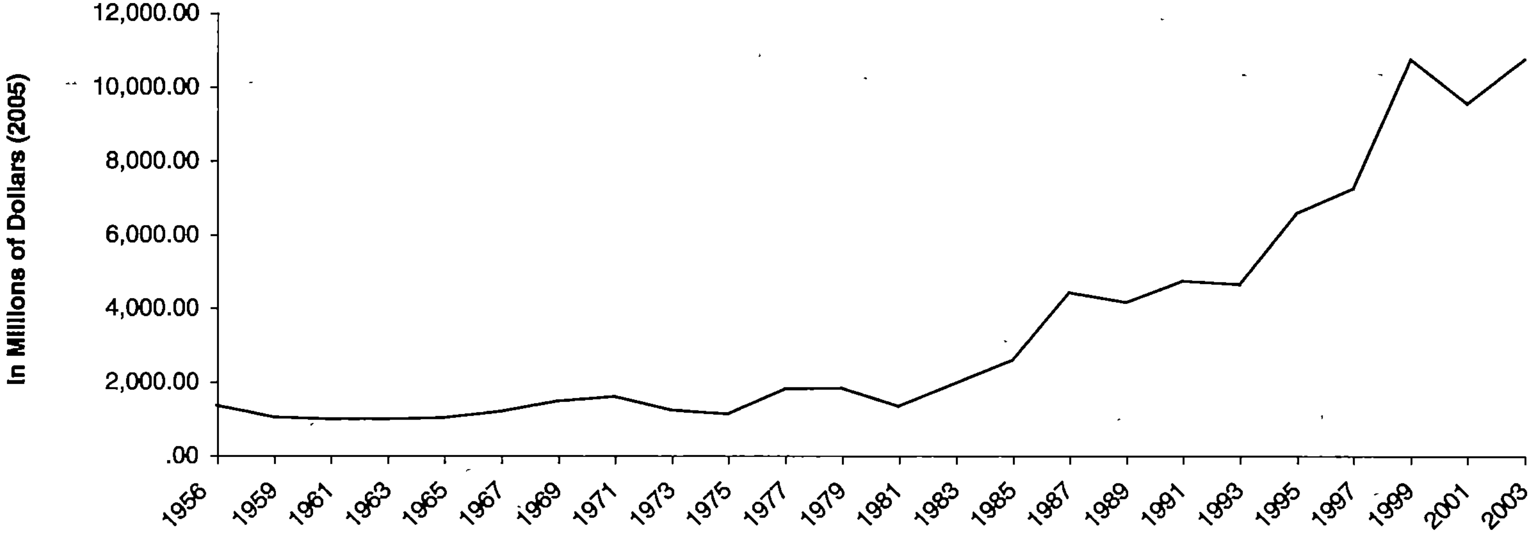
Control is defined to exist whenever one firm has authority or influence over decisions made by another firm (Heide and John 1990). In product development relationships, control takes two primary forms. First, development relationships are governed by *ex ante* contracts (i.e., development agreements) that vary in extensiveness from relationship to relationship. This article focuses on the detail and comprehensiveness of contractual specifications issued for the supplier's work as the measure of *ex ante* client control. Second, because most development tasks cannot be fully programmed in advance because of their uncertain and unfolding nature (Pisano 1990), *ex ante* contracts are usually accompanied by *ex post* control mechanisms. *Ex post* client control refers to ongoing control exercised during the performance of the supplier's work (e.g., Heide and John 1990; Stinchcombe 1985). Typical measures of *ex post* control in the channels literature focus on monitoring, reporting requirements, and decision-making influence.

Detailed descriptive studies of development agreements indicate extensive provisions for *ex post* client control in practice (Robinson and Stuart 2003). Importantly, these studies show that *ex post* control levels are determined in large part *ex ante* because *ex post* control rights are written into most development agreements. For example, monitoring and auditing rights, reporting requirements, positions on supervisory committees, and other factors that determine decision-making influence are explicitly stated in typical development agreements (Robinson and Stuart 2003).

Creativity may be defined succinctly as the generation of meaningful novelty (Andrews and Smith 1996; Hennessey and Amabile 1988; Jackson and Messick 1965; Ray and Myers 1986; Shalley 1991; Simon 1985). The term "meaningful" is used to distinguish goal-oriented creativity of the type required in business from abstract novelty of the kind often valued in more artistic endeavors (Amabile and Gitomer 1984; Ray and Myers 1986). This distinction notwithstanding, the generation of novelty is the central element of the construct and is the focus of measurement in most extant empirical work (e.g., Andrews and Smith 1996).

The focus in this article is on the creative nature of the task as the predictor of governance. The creative nature of the task is the extent to which the task requires the supplier to be creative to perform the work successfully. Tasks assigned to suppliers will differ in their nature along a continuum from creative to noncreative, and the current theory assumes that clients anticipate the nature of the task *ex ante* and implement governance structures accordingly. When measuring the creative nature of the task, the activities assigned to the supplier are specifically examined rather than the creative or noncreative nature of the overall development project. This is an important distinction because in many cases, the critical creative steps in outsourced new product development occur either before the engagement of the supplier (i.e., in formulating specifications of the supplier's work) or after delivery from the supplier; the supplier's work itself is relatively programmable.

FIGURE 1
Outsourced Development Spending by U.S. Firms (1956–2003)



Source. National Science Foundation (2005) Survey of Research and Development in Industry.

Notes: The graph represents nonfederally funded research and development contracted to outside organizations by U.S. firms. It excludes activities contracted to organizations outside the United States.

The organizational creativity literature identifies numerous factors that improve task performance when tasks are highly creative in nature. The list is broad and includes integration and coordination, reciprocity or mutual helpfulness, horizontal communications, cross-functional teams, intrinsic rewards, diversity of experiences and backgrounds within the team, a tolerance for conflict, limited formalization, high professionalism, positive attitudes toward risk and change, slack resources, environmental scanning, specialization, managerial tenure, technical and market knowledge, resource sufficiency, challenging work, and organizational encouragement of creativity (Amabile et al. 1996; Andrews and Smith 1996; Damanpour 1991; Glaser 1963; Hage and Aiken 1967; Marcson 1960; Merton 1957; Pierce and Delbecq 1977; Shepard 1956; Thompson 1965).

However, the most commonly identified factor is the absence of outside control (Amabile and Gitomer 1984; Bailyn 1985; King and West 1987; Paolillo and Brown 1978; Pelz and Andrews 1966; West 1987). Outside control has been linked to various negative effects on organizational decision making that tend to limit the ability to perform creative tasks. Among the effects detailed in the literature, control limits the supplier's discretion and ability to apply its expertise in creative problem solving (Andrews and Smith 1996; Thompson 1965). Control also leads to greater formalization in relationship governance and requires "up-and-over" information flows (Zaltman, Duncan, and Holbek 1973), both of which tend to limit horizontal communications and the ability to perform creative work. Likewise, a supplier's risk taking and novel idea generation are constrained in the presence of outside control because of pressures introduced by external evaluations, especially if these are confrontational in nature (Amabile 1979, 1998; Amabile, Goldfarb, and Brackfield 1990; Amabile et al. 1996; Cummings 1965; Delbecq and Mills 1985; Ettlie 1983; Hage and Dewar 1973; Hogarth 1980; Kanter 1983; Kim 1990; Kimberly and Evanisko 1981; Parnes 1964; Parnes and Meadow 1959; Sonnenberg 1991; Thomas and Velthouse 1990).

In addition to these effects, client control can also limit the supplier's ability to perform creative tasks through its effect on intrinsic motivation (Amabile 1979, 1983; Deci and Ryan 1985). It is well known that creativity requires substantial motivation (Amabile 1983; Andrews and Smith 1996; Hogarth 1980), and research suggests that intrinsic motivation (derived from an interest in and passion for performing the work itself) has a greater effect on the performance of creative work than does extrinsic rewards (Amabile 1988; Deci and Ryan 1980; Shalley 1991; Spiro and Weitz 1990). Intrinsic motivation is driven by several factors. However, control of decisions made in performing the work is significant among these because of the challenge and potential satisfaction it offers to the people involved (Amabile 1983, 1998; Thomas and Velthouse 1990).

Taken together, these ideas suggest that client control is more detrimental to supplier task performance in relationships in which the outsourced task is more creative in nature. To translate this logic into formal hypotheses, it is important to observe that the detrimental effects of client control on supplier performance are posited only to the extent that the task is creative in nature; client control is not expected to unduly limit the performance of tasks that require little or no creativity. Thus, main-effect relationships between client control and a posteriori supplier performance (including actual creativity) cannot be examined without consideration of whether the task called for creativity in the first place. Rather, the hypotheses are stated as interactions in which the creative nature of the task and the way it is controlled interact to determine the supplier's task performance. That is, the creative nature of the task negatively moderates the relationship between client control and supplier performance.

H_1: The interaction between *ex ante* client control and the creative nature of the task is negatively related to supplier task performance.

H_2: The interaction between *ex post* client control and the creative nature of the task is negatively related to supplier task performance.

Client Control Decisions

It is important to observe that the levels of *ex ante* and *ex post* client control involved in H_1 and H_2 are endogenously determined. When clients decide how much control to exercise, they are expected to assess the creative or noncreative nature of the task and anticipate the effects of their control on subsequent supplier performance. Therefore, clients are expected to exhibit less control in relationships in which the outsourced task is more creative in nature to avoid the negative effects on supplier task performance detailed previously. The argument here is precisely as before, the only difference being the added assumption that clients will anticipate the impact of their control on supplier performance and adjust their decisions accordingly.

H_3: The creative nature of the task is negatively related to *ex ante* client control.

H_4: The creative nature of the task is negatively related to *ex post* client control.

Additional Variables

Several additional variables are included in the models to enhance the managerial relevance of the results and account for certain predictors of governance identified in the extant literature. These are discussed in the following subsections.

Client skills. Amabile (1983) and others suggest that skills (i.e., know-how) are a critical input to creativity. A natural question that arises from this observation is whether the aforementioned detrimental effects of outside control are moderated by the client's task-related skills. In particular, might the harmful effects of client control on the performance of creative work be nullified or even reversed if the client exercising such control were highly skilled and thus more capable of competently managing and participating in the work? This possibility is important from a managerial perspective; it should not be concluded that client control universally harms supplier performance of creative work if this applies only to unskilled clients.

An explanation for the potential benefits of greater control by skilled clients can be found in certain theories within the creativity literature itself. According to these theories, creative outcomes result primarily from the novel combination of existing ideas (e.g., Amabile 1998; Amabile et al. 1996; Andrews and Smith 1996; Bartunek, Gordon, and Weathersby 1983; Bartunek and Moch 1987; Dougherty 1992; Osborn 1963). In general, this "building-block" perspective favors the inclusion of more parties in problem solving to increase the total stock of ideas available for generating novel combinations (Amabile 1983; Koestler 1964; Newell and Simon 1972; Olson, Walker, and Ruekert 1995). Thus, if clients are highly skilled, they can use their control to contribute unique and valuable ideas to the mix that could counteract other negative effects and actually increase the supplier's performance. A measure of client skills is included in both the supplier performance and the client control models to capture the effects of this variable.

Transaction-specific investments. Although the creativity literature typically counterindicates outside control of creative tasks, it is based largely on individual and intraorganizational research. In practice, firms may not be so willing to cede control in interorganizational relationships because of the dispersion of activities across independent firms that are subject to their own self-interests and prone to opportunism.

As Pisano (1990), Ulset (1996), and others discuss in detail, client investments in external product development relationships tend to be highly transaction specific (i.e., nonredeployable, nonsalvageable). Transaction-specific investments have been associated with an increased risk of *ex post* opportunistic bargaining over economic rents in a wide array of channels studies (e.g., Anderson 1988; Rindfleisch and Heide 1997). In the product development context, recent empirical research suggests that *ex post* bargaining is surprisingly common. For example, in a study of 200 development relationships, Lerner, Shane, and Tsai (2003) estimate probabilities of *ex post* bargaining before planned completion dates at between 37% and 58%, depending on exogenous conditions.[1]

Transaction cost analysis suggests that external development relationships should be governed with relatively high levels of client control to safeguard the client's transaction-specific investments against opportunistic bargaining and maintain the client's incentives to undertake efficient levels of external development (Williamson 1985). Observe that in the current context, greater client control is prescribed because the client makes the primary investment in sponsored development relationships. In the data, the mean client investment per relationship is approximately six times larger than the mean supplier investment (offsetting or reciprocal investments are not common safeguards in these relationships because of this one-sided investment pattern). A measure of the client's transaction-specific investments is included in the client control models to capture possible effects of this variable on governance selection.

Environmental uncertainty. Environmental uncertainty is defined as the frequency of unpredictable change in the task environment (John and Weitz 1988). Uncertainty has been commonly used as a predictor of governance selection in the channels literature, with mixed results (Rindfleisch and Heide 1997). Transaction cost analysis predicts a negative relationship between environmental uncertainty and *ex ante* control because contracts must be left incomplete to facilitate *ex post* adaptation in rapidly changing environments. The theory predicts a positive relationship between environmental uncertainty and *ex post* client control given the one-sided investment pattern in the data (e.g., Anderson 1985). The explanation for this relationship is that uncertainty increases the risk of opportunism by increasing the frequency of *ex post* adjustments, prompting greater safeguarding through *ex post* client control. In contrast, other studies in the incomplete contracting and organization theory literature posit a negative relationship between environmental uncertainty and *ex post* client control (e.g., Crocker and Reynolds 1993; Galbraith 1977). The argument here is that firms must reduce their span of control in more uncertain environments to enhance strategic flexibility and/or reduce their information processing burden. A measure of uncertainty is included in the client control models to account for such effects on governance selection.

History of prior relationships. The relational governance literature emphasizes the importance of prior relationships in developing norms and trust between parties over time (Dwyer, Schurr, and Oh 1987). Such relational norms can supplant formal control mechanisms in channel relationships. Thus, it is possible that the selection of both *ex ante* and *ex post* client control will depend on the history of relationships between the firms.

Relationship duration. The duration of the relationship can also have an effect on client control. Williamson (1985) suggests that more frequent exchange warrants more elaborate safeguards, such as control. Although product development relationships do not involve discrete exchanges, the duration of the relationship captures a similar property of the exchange, and this variable is included in the client control models to account for its effect on governance selection.

Method

The hypotheses are tested on a sample of 147 client-sponsored new product development relationships. Client organizations serve as the primary key informants because they are responsible for setting up, managing, and evaluating the performance of development relationships.

Data collection efforts were complicated by two factors, which became clear during a series of 12 field interviews and were later confirmed during preliminary telephone conversations with informants. First, knowledge about development relationships is concentrated within the firm. This prompted a search for only the single most qualified informant from the client organization. Typically, several referrals were necessary to reach this person, and as a result, the modal respondent in the data holds the rank of vice president. Second, supplier relationships are considered a key source of competitive advantage for many of the clients. Because of the sensitive nature of development work, most clients were reluctant to share the identity of the supplier beyond a general description. This reluctance has been observed elsewhere (Engardio et al. 2005). Thus, although it was the intention to pursue a matched supplier-side data collection at the outset, this effort was abandoned. As a result, common method variance is controlled for in the estimation. Specific job titles for the informants include research-and-development (R&D), engineering, marketing, and product development managers.

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[1] The relationships continued following these renegotiations. In other words, the high probabilities are not driven by relationship terminations.

Sampling Frame and Response Rates

To ensure a sufficient number of outsourced development projects in the sampling frame, data from the National Science Foundation (2005) Survey of Research and Development in Industry were used. The top five two-digit Standard Industrial Classification (SIC) code industries in terms of R&D intensity (R&D/sales) were selected, and then the top five three-digit industries from within this group in terms of the percentage of firms outsourcing R&D were selected. The final sampling frame consists of drugs and medicines (283); optical, surgical, and photographic instruments (384–387); communications equipment (366); motor vehicles and equipment (371); and aircraft and missiles (372, 376).

A random list of 2600 managers within the selected industries was obtained from a national list broker, with a single manager per firm. Attempts were made to contact each of these individuals to solicit the participation of their company. After a potential key informant was qualified using Campbell's (1955) criteria, they were asked to identify a product development project in which their firm had engaged an independent supplier to perform work that was financially sponsored by the client. To ameliorate problems of social desirability (Montoya-Weiss and Calantone 1994), informants were asked to select the relationship they were most familiar with, regardless of its success. A questionnaire, which required about an hour to complete, was then mailed to them.

Of the 2600 names on the list, 635 (24%) were invalid because either the company did not exist or the individual was no longer employed by the company. In the latter case, a referral to another person was requested. Another 670 (26%) could not be reached after an extensive effort. Again, an alternative contact was sought at the company. Among people successfully contacted by telephone, 226 (9%) reported that no R&D was conducted in their company. Substantially more people, 496 (19%), indicated that their company performed R&D but did not outsource these activities. This number is on par with expectations based on the National Science Foundation (2005) survey. Another 168 (6%) were involved with outsourced R&D projects but refused to participate. This left 405 (16%) qualified informants who verbally agreed to participate in the mail questionnaire. Of the 405 mailed questionnaires, 147 usable surveys were returned (36% of 405 mailed). This return rate is on par with rates from similar interorganizational studies (e.g., 30% in Heide and John 1990).

As Armstrong and Overton (1977) suggest, nonresponse bias was assessed by comparing early and late respondents across all variables in the study. No significant differences were found across the groups. As a second check, responding and nonresponding firms were compared in terms of their primary three-digit SIC code. The SIC code failed to significantly predict response.

Measures

Ex ante and ex post client control. Client control is defined as the extent to which the client exhibits authority or influence over the supplier's decisions (Heide and John 1990). As discussed previously, both *ex ante* and *ex post* client control were considered in this empirical study. *Ex ante* control is operationalized as a five-item scale that measures the detail and comprehensiveness of contractual specifications for the supplier's work (CONTRACT). Individual items address engineering and performance specifications, as well as specifications related to staffing and the overall development process and timeline. *Ex post* client control (CONTROL) is operationalized as a seven-item scale that measures the control the client exercised on an ongoing basis during the performance of the work. In line with the channels literature, individual items focus on monitoring, reporting requirements, and decision-making influence (e.g., Dwyer and Welsh 1985; Heide and John 1990; Ulset 1996). Client control in the form of integration (i.e., internalization) is excluded from the measure, given the context of the study. Appendix A contains items for all measurement scales.

Creative nature of the task (NATURE). The task is defined as creative in nature if it required the supplier to be creative to perform the work successfully. As discussed previously, this is an a priori characteristic of the task that is distinct from the supplier's subsequent a posteriori performance. The five items are adapted in part from the work of Andrews and Smith (1996). Work that is creative to one supplier may not be creative to another; thus, several items reference the specific supplier to tap this aspect of the construct domain.

Client skills (SKILLS). This eight-item scale measures the client's task-related skills. Informants were asked to consider skills at the outset of the relationship (i.e., not those learned during the project). Items focus on competencies embedded at the unit level and competencies embedded in individuals within the unit.

Transaction-specific investment (SPECIFIC). The client's transaction-specific investment in the development work is measured with a five-item scale adapted from the work of Anderson (1985), Heide and John (1988), and John and Weitz (1988). The scale items measure the client's investment in nonredeployable, nonsalvageable assets.

Environmental uncertainty. Environmental uncertainty is measured with two variables. Market uncertainty (MKTUNCT) refers to the frequency of change in the client's product markets relevant to the new technology. Five-items are adapted from the work of Jaworski and Kohli

(1993), Slater and Narver (1994), and Moorman and Miner (1997). Input uncertainty (INPUNCT) pertains to the frequency of change in the technologies used to perform the supplier's work.

History of relationships and relationship duration. These data were gathered with single items that asked for the time over which the firms had worked together on prior projects (PASTTIME) and the duration of the present project (DURATION). All projects are completed.

Supplier task performance (PERFORM). The supplier's a posteriori task performance is measured with a six-item scale that consists of two equally weighted dimensions taken from the new product development, R&D, and creativity literature. Informants were asked to evaluate the supplier's task performance on the basis of characteristics of the technology it delivered.

The first dimension pertains to the supplier's actual creativity on the task, as evidenced by the technology delivered (CREATIVE). The supplier's a posteriori creative performance is germane to this study and is also widely recognized as an important outcome in the broader new product development and R&D literature (e.g., Ancona and Caldwell 1992; Chang and Ibbs 1998; Griffin and Page 1993; Keller 1986; Olson, Walker, and Ruekert 1995; Song and Parry 1997).

The second dimension is adapted from the work of Gatignon and Xuereb (1997) and consists of three items that measure the expected contribution of the technology to the functionality, profitability, and competitiveness of the client's products (CONTRIB). This dimension measures the supplier's task performance by assessing the value of the technology it delivered to the client. Contribution is measured in terms of expectations the client formed after delivery of the technology because the full impact of newly developed technologies may not be reflected in more objective measures of product performance (e.g., sales), and such measures are also confounded by a large number of factors that are unrelated to the supplier's task performance.

Task performance is defined with two dimensions to enhance the managerial relevance of the performance measure and to ensure that the prescriptions arising from this study reflect both the creativity and the broader value of the technology to the client. The established new product development and R&D literature was followed by specifying an equally weighted additive model for the different dimensions of performance (e.g., Chang and Ibbs 1998; Griffin and Page 1993). In general, tasks that are more creative in nature should be associated with better performance. This is controlled for through the main effect between the creative nature of the task and supplier performance, which partials this relationship out of the relevant interactions. Note that the theory put forth in this study neither predicts nor places requirements on this main effect.

Estimation and Results

The empirical models are estimated using covariance structure analysis in Mplus 3. In line with the work of Anderson and Gerbing (1988), the measurement and structural models are estimated sequentially to reduce interpretational confounding and to limit complexity.

Measurement Model

A combined congeneric measurement model (Jöreskog and Sörbom 1989) is estimated for the multi-item scales with an additional common method factor, as Figure 2 illustrates. The common method factor loads on all items and may be viewed as an informant-specific factor that controls for variance and covariance among the items introduced by soliciting responses from a single informant. All trait variances are set to unity (Fornell and Larcker 1981).

Fit statistics for the model following purification also appear in Figure 2. The chi-square statistic is not significant ($p = .101$), suggesting an inability to reject the proposed model and an acceptable fit to the data. The root mean square error of approximation (RMSEA) is .028, safely below Browne and Cudeck's (1992) guideline of .05. The p value from the chi-square statistic may be viewed as the probability of H_0: RMSEA = 0. A test of the null hypothesis H_0: RMSEA $\leq .05$ yields a corresponding probability of .988, suggesting a high likelihood of acceptable model fit. Other fit statistics also suggest a reasonable fit for the complex measurement model.

Reliabilities and variance decompositions for each construct are given in Table 1 (see also Appendix B). Attenuated reliabilities are given in the first column and are all acceptable, exceeding the .6 guideline for composite reliability that Bagozzi and Yi (1988) suggest. Variance decompositions for each scale are given in the next three columns. Trait variance exceeds both method variance and error variance for all the scales.

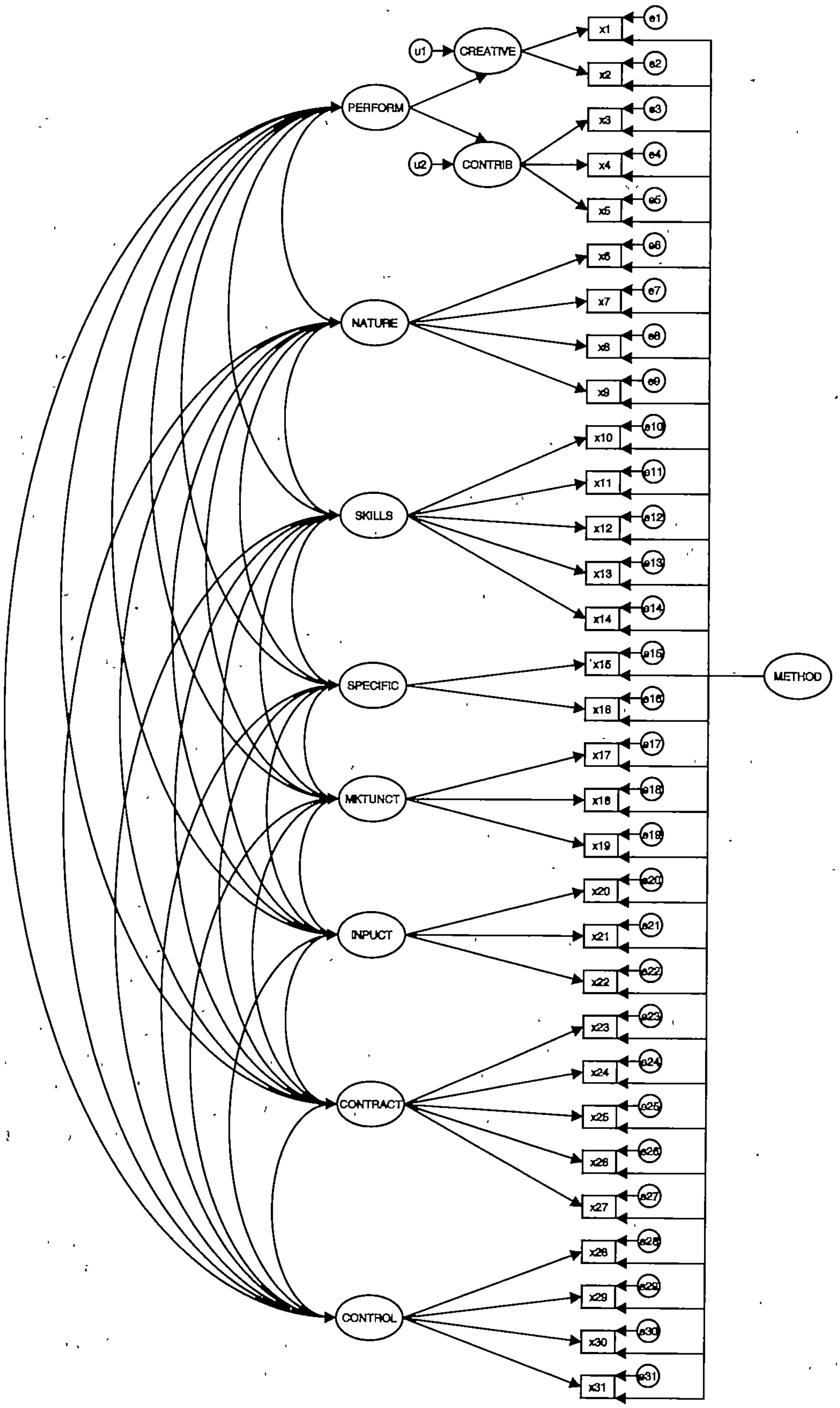
Discriminant validity is assessed in two ways. First, each intertrait correlation is constrained to unity, and differences in chi-square values between constrained and unconstrained models are examined. All test statistics are significant ($p < .05$), implying discriminant validity. Second, the attenuated average (trait) variance extracted (AVE) is computed in the final column of Table 1. Fornell and Larcker (1981) suggest that discriminant validity is established for a construct if its AVE is larger than its squared correlation with any other construct. The lowest AVE is .504 for market uncertainty, and the highest squared intertrait correlation is .200 between market and input uncertainty. Thus, the condition for discriminant validity is satisfied for all constructs. Descriptive statistics for the summed indicators and intertrait correlations following purification appear in Table 2.

Structural Models

The structural models are estimated using summed indicators for the constructs and include a common method factor that loads on all indicators. Indicators are mean-centered before analysis. For each indicator, the trait loading is fixed at $s \times \sqrt{T}$, the method factor loading is fixed at $s \times \sqrt{M}$, and the error variance is set to $s^2 \times E$, where s^2 is the variance of the summed indicator and T, M, and E are the percentages of trait, common method, and error variance from Table 1.

The structural models for client control are formulated as follows:

FIGURE 2
Congeneric Measurement Model with Common Method Factor



Notes: $\chi^2(374) = 409.301$, $p = .101$; goodness-of-fit index = .842; comparative fit index = .978; Tucker–Lewis index = .971; RMSEA = .028; and the probability that the RMSEA $\leq .05 = .988$.

TABLE 1
Reliabilities and Variance Decompositions for Multi-Item Scales

Scale	Final Items	Attenuated Reliability[a]	Trait[b]	Method[c]	Error[d]	Attenuated AVE[a]
CONTROL	4	.810	.800	.012	.188	.522
CONTRACT	5	.880	.855	.029	.116	.610
NATURE	4	.834	.824	.012	.164	.627
SKILLS	5	.938	.906	.034	.060	.759
PERFORM	5	.885	.779	.120	.101	.591
SPECIFIC	2	.683	.669	.021	.310	.520
MKTUNCT	3	.833	.660	.208	.132	.504
INPUNCT	3	.788	.690	.124	.186	.557

[a] Attenuated for common method variance/covariance in the items.
[b] Percentage of variance explained by trait (construct).
[c] Percentage of variance explained by common method factor.
[d] Percentage of variance explained by error.

TABLE 2
Descriptive Statistics and Intertrait Correlations

	M	SD	1	2	3	4	5	6	7	8	9	10
1. PERFORM	23.479	5.948	1.000									
2. NATURE	16.306	5.057	.419**	1.000								
3. SKILLS	17.380	7.914	−.274**	−.053	1.000							
4. SPECIFIC	10.090	2.878	−.008	.201*	.067	1.000						
5. MKTUNCT	12.644	3.989	.164	.100	.117	.010	1.000					
6. INPUNCT	8.181	3.981	.161	.447**	−.054	.263**	.272**	1.000				
7. CONTROL	18.132	5.062	.058	−.090	.141	.166	−.055	.120	1.000			
8. CONTRACT	22.306	5.924	−.032	−.220*	.042	−.023	−.017	−.059	.428**	1.000		
9. PASTTIME	26.844	38.016	.041	−.107	.051	.137	.104	−.027	.129	.200*	1.000	
10. DURATION	18.722	24.784	.180*	.245**	.079	.210*	−.121	.287**	.092	−.036	−.019	1.000

*Significant at $\alpha = .05$ (two-tailed).
**Significant at $\alpha = .01$ (two-tailed).

$$\text{(1)} \quad \text{CONTRACT} = \gamma_1\text{NATURE} + \gamma_2\text{SKILLS} + \gamma_3\text{SPECIFIC} + \gamma_4\text{MKTUNCT} + \gamma_5\text{INPUNCT} + \gamma_6\text{DURATION} + \gamma_7\text{PASTTIME} + \mu, \text{ and}$$

$$\text{(2)} \quad \text{CONTROL} = \alpha_1\text{NATURE} + \alpha_2\text{SKILLS} + \alpha_3\text{SPECIFIC} + \alpha_4\text{MKTUNCT} + \alpha_5\text{INPUNCT} + \alpha_6\text{DURATION} + \alpha_7\text{PASTTIME} + \eta,$$

where μ and η are residuals. Equations 1 and 2 are estimated using standard maximum likelihood.

Estimation of the supplier performance model is complicated by two factors. First, the model specifies latent variable interactions that are nonnormally distributed. This violates the distributional assumptions of the standard maximum likelihood estimator and can lead to serious underestimation of standard errors in practice (Jöreskog and Yang 1996). Klein and Moosbrugger (2000) provide a simulated maximum likelihood estimator that explicitly models the nonnormality and has been shown to produce unbiased, efficient estimates in finite samples. This estimator is used in Mplus 3 with Monte Carlo integration based on 1000 draws to estimate the supplier performance model. Although not immediately obvious, the imposed loadings of the common method factor on the construct indicators are reflected in the interactions by means of this method.

The second complication results from self-selection (e.g., Masten 1993). As discussed previously, clients select levels of control in Equations 1 and 2, in part, to maximize performance. This results in censored data in the supplier performance model, such that only maximizing choices are observed. Garen (1984) provides an estimator to control for self-selection that is analogous to Heckman's (1979) method but for continuous choice variables. The estimator is easily implemented by augmenting the supplier performance model with the first-stage structural residuals from the CONTRACT and CONTROL models, which are calculated from the factor scores and coefficients in Equations 1 and 2.

After augmentation, the structural model for supplier performance is as follows:

$$\text{(3)} \quad \text{PERFORM} = \beta_1\text{CONTRACT} + \beta_2\text{CONTROL} + \beta_3\text{NATURE} + \beta_4\text{SKILLS} + \beta_5\text{NATURE} \times \text{CONTRACT} + \beta_6\text{NATURE} \times \text{CONTROL} + \beta_7\text{NATURE} \times \text{SKILLS} \times \text{CONTRACT}$$

$$
\begin{aligned}
&+ \beta_8 \text{NATURE} \times \text{SKILLS} \times \text{CONTROL} \\
&+ \beta_9 \text{SKILLS} \times \text{CONTRACT} \\
&+ \beta_{10} \text{SKILLS} \times \text{CONTROL} \\
&+ \beta_{11} \text{NATURE} \times \text{SKILLS} + \beta_{12}\hat{\mu} + \beta_{13}\hat{\eta} + \varepsilon,
\end{aligned}
$$

where $\hat{\mu}$ and $\hat{\eta}$ are the structural residuals from the first-stage estimation of Equations 1 and 2. Note that β_5 and β_6 are the coefficients of interest in H_1 and H_2. The additional interactions with client skills were included to investigate the moderating effects of this variable on the client control–supplier performance relationships.

Supplier Performance Results

H_1. H_1 posits that there is a negative interaction between NATURE and CONTRACT. Rather than a negative coefficient, however, a significant and positive coefficient is observed for this interaction in Table 3. Thus, the results indicate that the creative nature of the task positively moderates the relationship between *ex ante* client control and supplier performance. Managerially, this implies that highly creative tasks should be governed with more *ex ante* client control, not less. This unexpected result is a major empirical insight of the study and is discussed in greater detail subsequently. No other coefficients involving *ex ante* control are significant in the supplier performance model.

H_2. H_2 posits tht there is a negative interaction between NATURE and CONTROL. This hypothesis is supported in the data. The creative nature of the task negatively moderates the relationship between *ex post* client control and supplier performance, as expected. The divergent results for H_1 and H_2 demonstrate that there are important differences between *ex ante* and *ex post* control in terms of their impact on the performance of creative tasks. Note that though the relationship is as hypothesized, other moderating effects on the *ex post* client control–supplier performance relationship exist in the data that must be considered when formulating managerial prescriptions based on the results. These involve client skills.

Client skills. The two three-way interactions with client skills were included to investigate the moderating effect of this variable on the interactions in H_1 and H_2. The NATURE × SKILLS × CONTRACT interaction is not significant ($p = .128$), suggesting that the relationship in H_1 is not significantly moderated by client skills. Substantively, this indicates that both skilled and unskilled clients benefit equally from using more detailed specifications to govern highly creative tasks.

The NATURE × SKILLS × CONTROL interaction is also not significant ($p = .174$). The insignificance of this three-way interaction similarly suggests that the relationship in H_2 is not significantly moderated by client skills. Thus, regardless of client skill level, the creative nature of the task negatively moderates the relationship between *ex post* client control and supplier performance.

The results are complicated by the SKILLS × CONTROL interaction, which is significant and positive in the data. Importantly, this indicates that the relationship between *ex post* client control and supplier performance is positively moderated by client skills, in addition to the negative moderating effect of the creative nature of the task. The positive direction of this relationship indicates that more skilled clients are better able to exercise *ex post* control. Observe that this moderating effect is independent of the creative or noncreative nature of the task but nevertheless effects managerial prescriptions because it can additively offset the negative moderating effects associated with task creativity. Thus, although client skills do not directly moderate the effect posited in H_2 (i.e., the creative nature of the task negatively moderates the relationship between *ex post* client control and supplier performance equally at all skill levels), client skills exhibit an independent moderating

TABLE 3
Structural Model Estimates: Supplier Performance

Independent Variables	**Dependent Variable** **PERFORM**
CONTROL	.221** (.132) $p = .047$
CONTRACT	.013 (.150) $p = .466$
NATURE	.614*** (.118) $p = .001$
SKILLS	−.327*** (.110) $p = .002$
NATURE × CONTROL	−.315** (.147) $p = .017$
NATURE × CONTRACT	.274** (.128) $p = .018$
NATURE × SKILLS × CONTROL	−.098 (.104) $p = .174$
NATURE × SKILLS × CONTRACT	.173 (.152) $p = .128$
SKILLS × CONTROL	.210** (.098) $p = .017$
SKILLS × CONTRACT	−.155 (.170) $p = .182$
NATURE × SKILLS	.197* (.129) $p = .065$
$\hat{\eta}$	.018 (.101) $p = .430$
$\hat{\mu}$	−.068 (.111) $p = .270$
Log-likelihood	−1962.482***

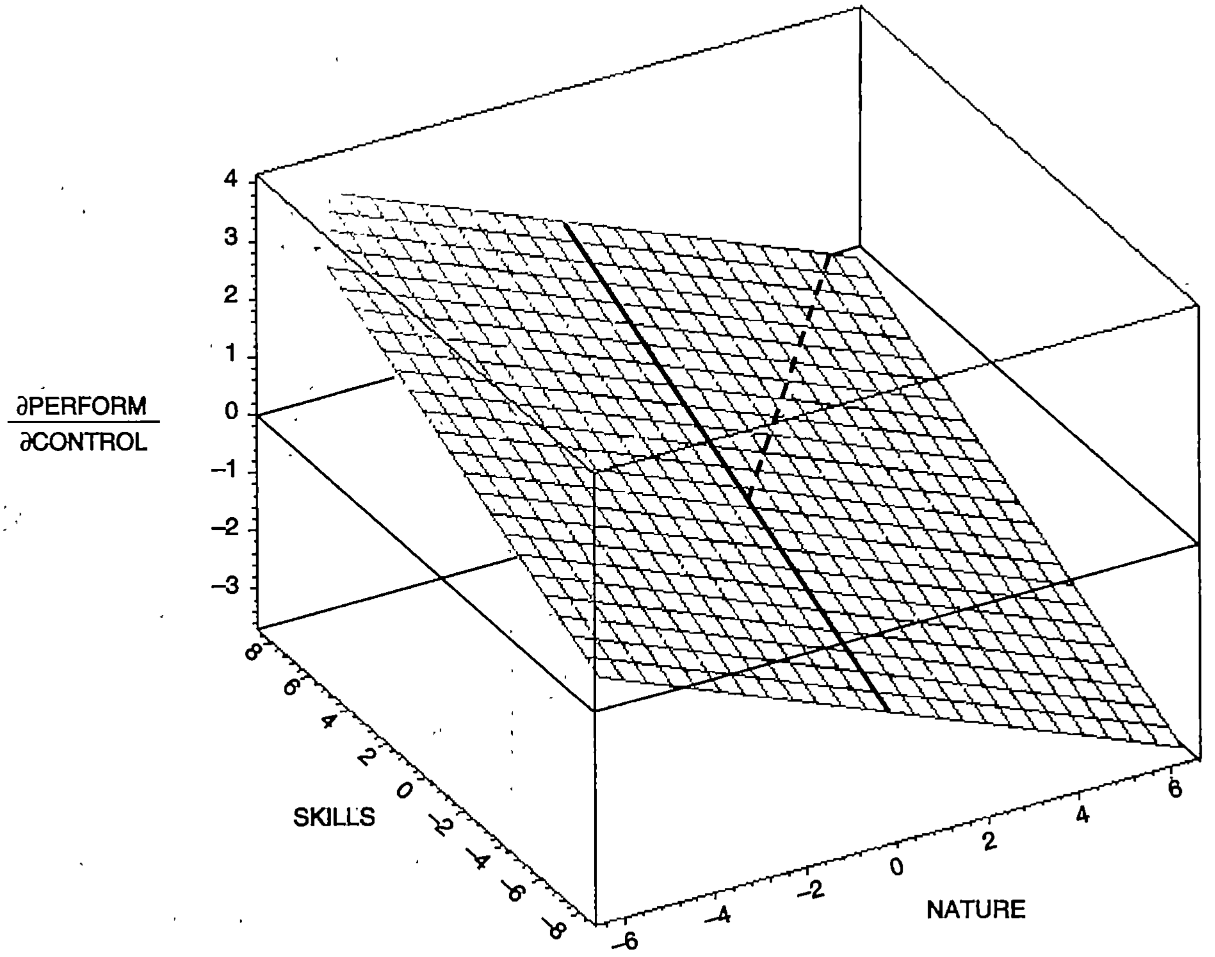
*$p < .10$ (one-tailed).
**$p < .05$ (one-tailed).
***$p < .01$ (one-tailed).
Notes: Standard errors are in parentheses. Independent variables explain 24.0% of the variance in PERFORM.

effect that must be considered when deriving managerial implications.

Figure 3 illustrates the complex relationship between *ex post* client control and supplier performance. The overall effect of *ex post* client control on supplier performance tends to be negative when the task is highly creative in nature and client skills are low. In contrast, the relationship tends to be positive when the task is not very creative in nature and client skills are high. This study is primarily concerned with tasks that require a high degree of creativity from the supplier. Conservatively, these are tasks that are above the mean on NATURE, as indicated by the heavy solid line in Figure 3. For these tasks, *ex post* client control tends to have a negative effect on supplier performance, except for certain highly skilled clients, as indicated by the dashed line. As the creative nature of the task increases in Figure 3, the number of these exceptional cases decreases, until eventually the relationship between *ex post* client control and supplier performance is negative over the full range of client skills. Thus, although the results for *ex post* client control are complex, they are consistent with the fundamental claim that *ex post* client control is detrimental to the performance of highly creative tasks, at least for the majority of clients in the data.

Finally, the main effects of NATURE and SKILLS are significant, as is their interaction. As expected, tasks that require greater creativity on the part of the supplier tend to produce more novel and valuable technologies, resulting in greater supplier performance. Similarly, the negative main effect of client skills suggests that tasks that are very *different* from the client's core skills (i.e., experiences) tend to produce more creative and valuable technologies and better supplier performance from the client's point of view. The positive interaction between the creative nature of the task and client skills suggests that independent of client control, client skills tend to improve supplier performance to the extent that the task is highly creative in nature. Observe that this is consistent with the building-block notion that the performance of creative tasks can be enhanced through the combination of ideas from different parties, as long as they possess the necessary skills to contribute meaningful inputs during creative problem solving.

FIGURE 3
Relationship Between *Ex Post* Client Control and Supplier Performance



Notes: NATURE and SKILLS plotted over +/− two standard deviations. Variables are mean-centered as in estimation The Z-axis gives the relationship between *ex post* client control and supplier performance.

The two selection-correction effects are not significant. This suggests that selection effects on performance are not strong in the data, despite the significant predictions in the client control models (estimates for the supplier performance model appear in Table 3).

Client Control Results

H_3. H_3 predicts that there is a negative relationship between NATURE and CONTRACT. An examination of the model for *ex ante* client control in the first column of Table 4 indicates support for this hypothesis. Clients exercise less *ex ante* control in relationships in which tasks are more creative in nature. Although this relationship is as hypothesized, it is important to emphasize that the result for H_1 indicates that this strategy may not be optimal in practice, because tasks that are highly creative in nature appear to benefit from greater *ex ante* control, not less.

H_4. H_4 predicts that there is a negative relationship between NATURE and CONTROL. This is supported in the *ex post* client control model, in which clients exhibit less *ex post* control in relationships in which the outsourced task is more creative in nature. In general, this strategy is consistent with the results from the performance model, except for highly skilled clients.

Other significant relationships. In the *ex ante* client control model, market uncertainty also exhibits a significant, negative relationship to *ex ante* client control. This is consistent with orthodox incomplete contracting theory, which predicts less complete contracts in more turbulent environments. The only other significant relationship involves the history of relationships between the two firms. The positive sign for history suggests that firms adopt more detailed and comprehensive specifications for their dealings over time as they develop a better understanding of each other. This is consistent with the view that contracts express mutual understandings that grow over time rather than safeguards that should decrease over time as norms and trust develop (Mayer and Argyres 2004). This viewpoint is taken in the subsequent theorizing on the role of contracts in improving the supplier's performance of creative tasks.

TABLE 4
Structural Model Estimates: Client Control

Independent Variables	Dependent Variable CONTRACT	 CONTROL
NATURE	−.306*** (.110) *p* = .003	−.248** (.111) *p* = .014
SKILLS	−.035 (.102) *p* = .367	.129 (.102) *p* = .103
SPECIFIC	−.095 (.122) *p* = .219	.131 (.122) *p* = .144
MKTUNCT	−.274* (.178) *p* = .064	−.241* (.154) *p* = .060
INPUNCT	−.111 (.152) *p* = .233	.171 (.141) *p* = .113
DURATION	.012 (.095) *p* = .451	.070 (.097) *p* = .235
PASTTIME	.202** (.096) *p* = .019	.121 (.098) *p* = .111
Log-likelihood	−2105.772	−2092.002

*$p < .10$ (one-tailed).
**$p < .05$ (one-tailed).
***$p < .01$ (one-tailed).
Notes: Standard errors are in parentheses. Independent variables explain 18.1% of the variance in CONTROL and 24.1% of the variance in CONTRACT.

Turning to the *ex post* client control model, the only additional relationship that is significant at conventional alpha levels is the negative relationship between market uncertainty and *ex post* client control. This is consistent with certain findings in the incomplete contracting and organization theory literature streams that emphasize a reduced span of control as a response to uncertainty (e.g., Crocker and Reynolds 1993; Galbraith 1977). The result is at odds with Williamson's (1985) safeguarding-based logic, which posits a positive relationship. As Rindfleisch and Heide (1997) observe, the results supporting both positions are common in the empirical literature.

With respect to safeguarding, note that the client's transaction-specific investments do not significantly predict either *ex ante* or *ex post* client control, as would be expected if client control were being used primarily as a safeguard. Development relationships place a far greater emphasis on creativity than do ordinary channel relationships. As a consequence, it appears that the creative nature of the task plays a more significant role in determining governance than do other considerations in these models (estimates for the two client control models appear in Table 4).

Discussion

The results provide important insights into the complex relationship between client control and supplier performance for creative tasks in new product development. The hypotheses pertaining to *ex post* client control are supported in the data. The results indicate that the creative nature of the task negatively moderates the relationship between *ex post* client control and supplier performance, as predicted. Mirroring this, less *ex post* client control is exhibited in relationships that involve tasks that are more creative in nature. An examination of the role of client skills shows that some highly skilled clients are able to overcome the negative effects of *ex post* control on the performance of creative tasks. However, as tasks become more and more creative in nature, clients must be increasingly skilled for this to occur. For exceptionally creative tasks, no level of client skill can compensate for the detrimental effects associated with *ex post* client control.

The results demonstrate that the protection of creativity is an important governance objective even in interorganizational relationships, in which the risk of opportunism might otherwise prompt firms to retain tight control of external suppliers. Indeed, the estimates suggest that the creative nature of the task has a stronger impact on client control decisions than do variables typically associated with safeguarding in the channels literature, such as transaction-specific investments. This does not mean that safeguarding is not a concern; however, the creative nature of the task appears to be a more significant consideration in predicting interorganizational governance arrangements in these models, and clients may sacrifice some level of safeguarding to protect the supplier's ability to perform creative tasks.

The primary empirical insight in the data pertains to the positive effect of greater *ex ante* contracting on supplier performance for tasks that are highly creative in nature. In the formulation of the hypotheses, there was no differentiation between *ex ante* and *ex post* control mechanisms in terms of their impact on the performance of creative work. This followed the universalistic approach to outside control taken in the majority of the creativity literature, which does not elaborate in detail on the different governance mechanisms through which control can be exercised. The data suggest that this undifferentiated approach is myopic. Instead, a differentiated theory in the spirit of the comparative governance literature is required to describe adequately the performance ramifications of contractual and noncontractual modes of control when applied to creative tasks. Thus, a theoretical explanation for the observed differences that draws on both the creativity and the incomplete contracting literature streams is offered.

Differentiating Between Ex Ante *and* Ex Post *Client Control*

Although the creativity literature does not differentiate between *ex ante* and *ex post* control, it draws a distinction between microlevel and macrolevel control. Microlevel control pertains to the individual steps through which objectives are accomplished, whereas macrolevel control focuses on setting the objectives themselves.

The creativity literature suggests that outside control is particularly detrimental to the performance of creative tasks when it extends to microlevel decision making, in part because of the negative effects of microlevel control on intrinsic motivation (Amabile 1983, 1998; Amabile and Gitomer 1984; Deci and Ryan 1985; Shalley 1991; Thomas and Velthouse 1990). In contrast, macrolevel control of task objectives is less damaging to the performance of creative work. Indeed, recent empirical research has suggested that clearly stated and unchanging objectives can actually improve the performance of creative tasks (Amabile 1994). Enhanced performance occurs through clarification of the client's objectives for the project, thus keeping the supplier's creative efforts on track with the client's needs, and through assurance that the supplier's exploratory efforts in pursuit of stated objectives will be valued by the client, which increases intrinsic motivation.

An important difference between *ex ante* and *ex post* control mechanisms is how they vary in their abilities to control development work at a microlevel. As is discussed at length in the incomplete contracting literature, contractual terms must be set in advance and are expressed formally (i.e., in writing), whereas *ex post* control does not require such forward rationality or formalization. Incomplete contracting theory indicates that parties subject to bounded rationality will not be able to anticipate future conditions adequately and formalize a plan of work in complex environments, such as product development. As a result, *ex ante* contracts are invariably incomplete (Anderson 1985; Heide and John 1988; Williamson 1985).

The incompleteness of *ex ante* contracting is usually considered a disadvantage relative to *ex post* control in the channels literature (e.g., Williamson 1985). However, a consequence of the incompleteness of *ex ante* contracts is that they do not typically legislate the details of the work at a microlevel. Instead, even detailed development contracts are typically limited to broad specifications that describe the client's goals for the project at a macrolevel. These specifications guide the supplier's work toward particular client objectives and place certain other broad requirements related to staffing and the overall development process and timeline on the supplier but do not usually specify microlevel details about the precise ways that objectives are to be accomplished. In contrast, *ex post* control is much more capable of guiding the work at a microlevel through monitoring and decision-making involvement as the work is performed. Indeed, this is one of the main reasons *ex post* control mechanisms are used to supplement *ex ante* contracts in practice (Williamson 1985). Although the fine-grained nature of *ex post* control is usually considered an advantage in the extant governance literature, the creativity literature suggests that the kind of microlevel control it allows tends to harm the performance of creative tasks.

Viewed through this lens, the empirical results suggest that *ex ante* contracting can enhance the performance of creative work in product development relationships by clarifying and fixing objectives at a macrolevel while avoiding interference with supplier decision making and intrinsic motivation at a microlevel. The benefits of setting objectives should be most pronounced for creative tasks because of the ambiguous, exploratory, and path-dependent nature of creative work, which makes it easy for suppliers to stray from objectives and lose motivation while progressing through the complex task. Indeed, this is evidenced in the data, such that the effect of *ex ante* control on supplier performance becomes more positive as the task becomes more creative in nature.

It is important to emphasize that this study's conclusion applies to creativity in the business context under study. More artistic forms of creativity may not similarly benefit from detailed specification of objectives, nor will some product development tasks that are so creative in nature that even the general goals are indefinable *ex ante*. Because greater contracting improves the performance of creative tasks, these kinds of indefinable tasks appear to be in the minority among outsourced development projects in this study, most likely because they are usually performed in-house.[2] In addition, the measure of *ex ante* contracting focuses specifically on specifications issued for the supplier's work. Specifications clarify and fix the client's objectives for the project, which can increase the performance of creative work. Other aspects of contracting—in particular, contracts that attempt to hold suppliers to a precise prespecified plan of work at a microlevel—are not likely to similarly benefit the performance of creative tasks.

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[2] This study investigated the possibility of a nonlinear relationship in which more extensive contracts first help and then hurt supplier performance as tasks become more creative in nature. No support was found for such a specification in the data.

Managerial Implications

The results suggest that the creative nature of the task should be carefully considered when designing interorganizational governance structures in product development and other creatively demanding areas. Greater *ex ante* client control in the form of detailed contractual specifications for the supplier's work improves the supplier's performance in relationships involving tasks that are highly creative in nature. In contrast, greater *ex post* client control tends to diminish the supplier's performance in these relationships, though highly skilled clients are able to overcome this effect. Skills exhibit no significant moderating effects with respect to *ex ante* client control. Thus, clients should expect to benefit from issuing more detailed contractual specifications for highly creative tasks regardless of their skill level.

The performance results are insightful in part because they conflict with certain observed managerial practices in the data. Clients scale back both *ex ante* and *ex post* control in relationships in which greater creativity is required on the part of the supplier. For *ex post* control, this practice is consistent with the performance results, except for highly skilled clients. However, this is not true for *ex ante* control. The results suggest that reducing *ex ante* client control of highly creative tasks actually produces less valuable technologies for the client.

The results of this study are consistent with other recent counterintuitive findings in the creativity literature (see Amabile 1994). Commenting on her ongoing research into intraorganizational creativity, Amabile (1998, p. 81) observes that clear objectives appear to increase the performance of creative work; she notes that "people will be most creative ... if you give them freedom to decide how to climb a particular mountain. You needn't let them choose which mountain to climb. In fact, clearly specified strategic goals often enhance people's creativity." Thus, she suggests that managers should articulate clear goals for creative projects and then allow team members discretion in deciding how to meet the goals (Amabile 1994). A similar conclusion is reached here in that outsourced creative tasks are best managed with detailed *ex ante* contractual specifications followed by relatively hands-off *ex post* control by most clients.

The negative effects of *ex post* control on highly creative tasks observed for most clients in the study are consistent with traditional arguments in the creativity literature, which suggest that outside control can decrease novel idea generation and risk taking on the part of the supplier, interfere with the supplier's ability and discretion to apply its expertise in creative problem solving, impose greater formalization in relationship governance, and limit the supplier's intrinsic motivation to develop creative solutions, among other effects. Clients outsourcing creative tasks should limit their *ex post* control to avoid such distortions, unless they have strong task skills that can compensate for the negative effects on creativity. Moreover, the differences between microlevel and macrolevel control alluded to in the literature suggest that clients should not only limit their *ex post* control of creative tasks in general but also restrict the *ex post* control they exercise to more broad-level guidance of the project.

Managerially, *ex ante* control can enhance creative performance in several ways. As discussed previously, detailed specifications can coordinate the supplier's creative efforts and improve the fit between the creative output and the client's needs without the creativity damaging effects of microlevel control. Specifications can also increase intrinsic motivation by assuring the supplier that the client will value its creative efforts. In addition, specifications that call for outcomes at the forefront of current technological capabilities can prompt greater creative efforts on the part of suppliers than they might otherwise pursue if left on their own. According to the literature on adaptive aspiration levels (e.g., Cyert and March 1992), performance targets often shrink when confronted with failure. Because creative work inevitably involves failures along the way, detailed specifications can help counteract this tendency and maintain a steady focus on desired outcomes.

The prescriptions arising from the study reflect certain features of creative tasks in the technology-driven industries included in the sample. Recall that these industries outsource product development most frequently. In high-technology product development, it is often easier to specify desired outcomes for new technologies in terms of functionality than to overcome creatively the technological barriers necessary to meet specifications *ex post*. Indeed, desirable attributes of new products are often recognized substantially in advance of the point at which technological advancement enables such features to be implemented. Thus, much of the creative work in these industries occurs in trying to meet specifications rather than in the formulation of the specifications themselves. Reflecting this, the data indicate that it is especially important for clients to exercise caution in controlling tasks *ex post* when the most creative acts typically occur. Detailed specifications, followed by decentralized management *ex post*, appears to produce the best outcomes for most clients in the data. As discussed previously, this conclusion must be tempered by the recognition that certain tasks will be so creative in nature that even general specifications cannot be written and that client skills can compensate for the detrimental effects associated with outside control of creative work, except for the most creative tasks.

Limitations and Conclusion

The study suffers from several limitations that must be considered in interpreting the results. A single informant methodology was used and data were collected from only the client side of the dyad. It is possible that a more balanced research design would shed additional light on the subject. In addition, performance was measured by client ratings. Although clients are certainly capable of assessing the supplier's performance, their ratings may be colored by perceptual error. It is also possible that clients in their ratings overreward suppliers for technologies that are in line with their objectives. Finally, the measure of *ex ante* control, which produced some of the more interesting results in the study, focused explicitly on specifications. As discussed previously, more microlevel aspects of *ex ante* contracts are unlikely to produce beneficial effects on the performance of creative tasks.

A key area for further research is the detailed study of alternative methods or styles of control. Are there means by which the client can exercise control in a manner that does not limit supplier performance for creative tasks or even enhances it? This study shows the surprising functioning of contractual specifications in this regard. Incentives generated through property rights and relational governance forms could be promising methods of control for creative tasks that would sidestep the distortions on supplier creativity associated with more hands-on forms of *ex post* control.

Control is not exercised trivially. Clients that desire control of supplier activities as a relationship safeguard must also consider the impact of their control, both good and bad, on supplier performance. The data provide the clearest evidence to date of the relationships among performance, the creative nature of the task, and the exercise of *ex ante* and *ex post* client control in outsourced development relationships.

APPENDIX A
Measurement Scale Items

CONTROL

1. The contractor's work was monitored closely by our people.
2. The contractor was required to file extensive reports on its work during the project.
3. We were closely involved with decisions that arose during the contractor's work.
4. We often required that the contractor perform its work a certain way.
5. We occasionally forced changes to the development plan or budget that were not desired by the contractor.[a]
6. We occasionally denied the contractor permission to do something they wanted to do.[a]
7. Frequent milestones were used in the relationship.[a]

CONTRACT

1. Technical or engineering specifications for the technology to be delivered.
2. Performance specifications for the technology to be delivered.
3. Specifications for the contractor's people assigned to your project.
4. Specifications for the processes to be employed in the contractor's work.
5. Specifications for milestones and/or milestone deliveries.

NATURE

1. To be considered a success, the technology produced by the contractor had to incorporate significant new knowledge.
2. It was unclear exactly what knowledge and capabilities would be needed to complete the contractor's work at the outset.[a]
3. To perform its work well, the contractor had to be inventive and discover how to do new things
4. The technology was only a slight departure from technology the contractor had produced before. (R)
5. The contractor's work demanded a lot of creativity and imagination.

SKILLS

1. The skills which were typical of our unit were very similar to the skills of the contractor.[a]
2. Most managers in our unit had prior personal experience with the type of work the contractor performed for us.[a]
3. The contractor's R&D work was very similar to work regularly done throughout our unit.
4. The skills needed to perform the contractor's R&D work were also a core competency of our unit.[a]
5. The R&D work for our most important products is very similar to the work the contractor was doing.
6. Most people in our unit had the same training and technical background as the contractor's people on our project.
7. Our unit was known for its successful performance of the type of work the contractor was doing.
8. Our internal R&D people had or could have easily learned the skills needed to perform the contractor's work.

PERFORM

1. The technology was very innovative.[a]
2. The contractor exhibited a great deal of creativity in its work.
3. The technology incorporated a great deal of new knowledge and discoveries.
4. The technology will contribute a great deal to the functionality of our products.
5. The technology will contribute a great deal to the competitiveness of our products.
6. The technology will contribute a great deal to the profitability of our products.

SPECIFIC

1. If we had to switch to a different contractor during the project much of our investment would have to be made again.
2. If we had to switch to a different contractor during the project it would take some time for us to bring the new contractor up to speed on the technology.
3. We spent a lot of time and effort learning to work effectively with the contractor before our relationship was productive.[a]
4. The project required close working relationships between the contractor's people and our people.[a]
5. We could easily complete work in-house if the relationship with the contractor broke down.[a] (R)

MKTUNCT

1. Customers' preferences for our products change constantly.
2. The technology in our products is rapidly improving.[a]
3. Our customers demand the very latest technologies.[a]
4. Our competitors rapidly advance their product technologies.
5. Nothing stays the same for long in our industry.

APPENDIX A
Continued

INPUNCT

1. The technologies involved in the contractor's R&D work were changing rapidly.
2. Frequent adjustments in the contractor's plan of work were called for to incorporate new technologies.
3. It was difficult to forecast the technological environment surrounding the contractor's R&D work.[a]
4. Technological breakthroughs developed in other areas altered how the contractor performed its work.

[a] Item was dropped during scale purification.

Notes: All items were measured with seven-point "strongly disagree/strongly agree" scales, except CONTRACT (five-point "very little detail/highly detailed"). R = reverse scored.

Appendix B

The variance decomposition reflects the percentage of variance in the summed indicator explained by the trait, common method factor, and error. For first-order factors with unity variances, the percentage of variance explained by the trait is given by

$$\text{(B1)} \qquad \frac{\left(\sum \lambda_T\right)^2}{\left(\sum \lambda_T\right)^2 + \left(\sum \lambda_M\right)^2 + \sum \theta_\varepsilon},$$

where λ_T and λ_M denote the loadings of the trait and method factor, respectively, the θ_ε are the item error variances, and summation is across all items in the scale. The percentages of variance explained by the method factor and error are calculated analogously. Attenuated reliability is calculated in the standard manner as

$$\text{(B2)} \qquad \frac{\left(\sum \lambda_T\right)^2}{\left(\sum \lambda_T\right)^2 + \sum \theta_\varepsilon},$$

where attenuation is due to the inclusion of the common method factor in the model, and attenuated AVE is calculated as

$$\text{(B3)} \qquad \frac{\sum \lambda_T^2}{\sum \lambda_T^2 + \sum \theta_\varepsilon}.$$

The AVE differs from both the percentage of trait variance in the scale and reliability because AVE does not count covariance among the scale items explained by the trait. The calculations for PERFORM are more complex because of the second-order factor structure and the need to weight the two subdimensions equally in the summed scale. Let the summary indicator be

$$\text{(B4)} \qquad Y = \sum_{i=1}^{n} a_i x_i,$$

where the x_i are the n scale items and the a_i are the weights assigned to each item. The variance in Y explained by the common method factor is given by

$$\text{(B5)} \qquad \left(\sum_{i=1}^{n} a_i \lambda_{M_i}\right)^2.$$

The variance in Y explained by error is given by

$$\text{(B6)} \qquad \sum_{i=1}^{n} a_i^2 \theta_{\varepsilon_i}.$$

The variance in Y explained by the trait may be straightforwardly calculated by summing these quantities and subtracting them from the estimated total variance in the summed weighted scale. The latter is calculated as

$$\text{(B7)} \qquad \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j \widehat{\text{cov}}\left[x_i, x_j\right],$$

where the covariance matrix is the fitted (implied) covariance matrix from the estimation.

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Bruce Cooil, Timothy L. Keiningham, Lerzan Aksoy, & Michael Hsu

A Longitudinal Analysis of Customer Satisfaction and Share of Wallet: Investigating the Moderating Effect of Customer Characteristics

Customer loyalty is an important strategic objective for all managers. Research has investigated the relationship between customer satisfaction and loyalty in various contexts. However, these predominantly cross-sectional studies have focused on customer retention as the primary measure of loyalty. There has been little investigation into the impact on share of wallet. Using data from the Canadian banking industry, this research aims to (1) provide the first longitudinal examination of the impact of changes in customer satisfaction on changes in share of wallet and (2) determine the moderating effects of customer age, income, education, expertise, and length of relationship. Data from 4319 households using 12,249 observations over a five-year period indicate a positive relationship between changes in satisfaction and share of wallet. In particular, the initial satisfaction level and the conditional percentile of change in satisfaction significantly correspond to changes in share of wallet. Two variables, income and length of the relationship, negatively moderate this relationship. Other demographic and situational characteristics have no impact.

Customer loyalty is an important strategic objective of managers around the world. A worldwide survey of chief executive officers conducted by the Conference Board (Bell 2002) found that customer loyalty and retention was the most important challenge that chief executive officers believed they faced. Despite managers' emphasis on loyalty, however, brand loyalty is widely reported to be declining (Chancy 2001). Compared with the more exclusive loyalty of the past, consumers increasingly hold polygamous loyalty to brands (Bennett and Rundle-Thiele 2005; Rust, Lemon, and Zeithaml 2004; Uncles, Dowling, and Hammond 2003; Uncles, Ehrenberg, and Hammond 1995). As a result, customers are increasingly dividing their purchases among multiple brands in a category. For example, Kraft Foods defines a loyal customer as someone who purchases 70% or more of the same brand within a category over three years. On the basis of this benchmark, 30 years ago, 40% of Kraft's customers would have been classified as loyal. Today, that number is closer to 15% (Zabin and Brebach 2004).

Jones and Sasser (1995, p. 94) assert that "the ultimate measure of loyalty ... is share of purchases in the category" (i.e., share of wallet). Although this may be an overstatement, because share of wallet is not as forward looking as other measures of loyalty (Oliver 1999), it is frequently used by researchers to operationalize loyalty behavior (e.g., Bowman, Farley, and Schmittlein 2000; Bowman and Narayandas 2004; Brody and Cunningham 1968; Cunningham 1956, 1961; Wind 1970). In an effort to increase customers' share of spending with a brand, managers have focused on improving customers' level of satisfaction. Rust (2002) explains the logic as follows: "Customer satisfaction and delight have a tremendous impact on customer retention and customer loyalty, and the result of that is that you keep customers around longer, and you also get a higher share of their wallet."

Early research supports the suggested link between satisfaction and share of wallet (Baumann, Burton, and Elliott 2005; Bowman and Narayandas 2004; Keiningham, Perkins-Munn, et al. 2005; Keiningham, Perkins-Munn, and Evans 2003; Perkins-Munn et al. 2005; Silvestro and Cross 2000). In managerial terms, the relevance of such a linkage is that changes in customers' levels of satisfaction are presumed to correspond to changes in customers' share-of-wallet allocations. Yet despite the widespread recognition that "marketers should examine changes in customer satisfaction over time" when evaluating satisfaction's impact on customer behavior (Bolton, Lemon, and Verhoef 2004, p. 277), research examining the relationship between satisfaction and share of wallet has disregarded temporal effects and has relied almost exclusively on cross-sectional (single

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point in time) data. Therefore, estimations of the impact of changes in satisfaction on share of wallet over time cannot comfortably be made, nor can inferences of causality.

In addition, research has found that the nature of the relationship between satisfaction and customer behavior (repurchase intention and retention) is moderated by the differentiating characteristics of various customer groups (e.g., age, sex, education) (Mittal and Kamakura 2001). Currently, however, no research exists that examines the effect of customer characteristics on the relationship between satisfaction and share of wallet.[1]

The objectives of this article are to (1) provide the first longitudinal examination of the association between customer satisfaction and customers' share of spending (share of wallet) and (2) test the moderating effect of customer characteristics on this relationship. The data used to investigate the proposed relationships consist of 4319 Canadian households whose banking relationships were tracked for a minimum of three years. Share of wallet represents the percentage of the business that households allocate to various financial institutions for different banking products/services across all financial institutions that the household uses.

Theoretical Background

Customer Satisfaction and Share of Wallet

Customer satisfaction has traditionally been regarded as a fundamental determinant of long-term consumer behavior (Oliver 1980; Yi 1990). Much of the research on customer satisfaction and customers' actual behavior has focused on the relationship between satisfaction and retention. This emphasis is largely the result of early research, which identified customer retention as a key driver of firm profitability (Reichheld 1993, 1996; Reichheld and Kenny 1991; Reichheld, Markey, and Hopton 2000; Reichheld and Sasser 1990).

Capraro, Broniarczyk, and Srivastava (2003, p. 164) observe that "today, most firm's programs to control customer defections center heavily on the management of customer satisfaction." Research appears to support this approach. Many studies have linked customer satisfaction to purchase behavior (Anderson and Sullivan 1993; Bolton 1998; Jones and Sasser 1995; LaBarbera and Mazursky 1983; Loveman 1998; Mittal and Kamakura 2001; Newman and Werbel 1973; Rust and Zahorik 1993; Sambandam and Lord 1995). Furthermore, the majority of researchers attempting to conceptualize and operationalize the chain of effects from satisfaction to profits have proposed models that link satisfaction to retention and retention to profits (e.g., Anderson and Mittal 2000; Heskett et al. 1994; Rust, Zahorik, and Keiningham 1995; Zeithaml, Berry, and Parasuraman 1996).

Recently, however, researchers and managers have begun to question fundamental aspects of the relationship between customer retention and firm profitability (Carroll 1991–1992; Carroll and Rose 1993; Coyles and Gokey 2002; Gupta and Lehmann 2005; Keiningham, Vavra, et al. 2005; Reinartz and Kumar 2000, 2002). One such question pertains to how loyalty is conceptualized and measured. Researchers and managers have become increasingly interested in consumers' share of spending as a behavioral measure of customer loyalty (Keiningham, Aksoy, et al. 2005; Uncles, Dowling, and Hammond 2003). For example, Zeithaml (2000, 76) notes a "growing popularity of the concept of 'share of wallet.'" Research conducted by McKinsey & Company also supports this change in focus from retention to share of wallet, and Coyles and Gokey (2002) find that efforts to improve customers' share of spending and customer retention can add as much as ten times greater value to a company than focusing on retention alone.

Marketing theory and empirical research lend credibility to this shift in focus. Zeithaml (2000) proposes a model in which customer retention leads to firm profits in one of four ways: (1) lowering costs to service customers, (2) the ability to charge premium prices, (3) word of mouth, and (4) increased volume of purchase (i.e., increased share of wallet). However, Reinartz and Kumar (2000, 2002) find that customer retention does not result in loyal customers costing less to serve, paying higher prices for the same bundle of services, or marketing the company through word of mouth. Therefore, this implies that the primary path from retention to firm profitability in Zeithaml's (2000) proposed model is through increased share of wallet.

Rust, Lemon, and Zeithaml (2004) also note that the way researchers have treated customer retention does not accurately portray customers' actual behavior patterns, observing that researchers frequently treat customers who defect as "lost for good." They argue that a "more realistic scenario" is that customers may leave and return and be either serially monogamous or polygamous in terms of the number of firms with which they conduct business in the category. This treatment of retention closely mirrors the concept of share of wallet. The observation that consumers continuously leave and return to a product, service, or institution over a period of time is consistent with commonly used measures of share of category spending (Stern and Hammond 2004). Typically, consumers' share of spending across a broad range of business sectors is measured as the share of purchases customers provide to a particular brand in the category over a fixed period (Cunningham 1956; Jones and Sasser 1995; Zabin and Brebach 2004).

Retention and share of wallet, though not identical, are closely related. The finding that consumers engage in serially monogamous or polygamous relationships with companies unequivocally implies a close link between retention/repurchase and share of category spending (share of wallet).

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[1] This study examines share of wallet rather than retention or loyalty. Indeed, there is a relationship among share of wallet, retention, and loyalty, but they are distinct constructs in the literature. Simplistically, definitions for the three can be understood as follows: Share of wallet is the percentage of money a customer allocates in a category that is assigned to a specific firm. Retention is a measure of the continuance of a relationship with a firm (i.e., it can be only 0 or 1). Loyalty is "a deeply held commitment to rebuy or re-patronize a preferred product/service in the future" (Oliver 1999, p. 34). As such, loyalty is a multidimensional construct. There is no universally accepted definition of loyalty in the literature, but it is typically believed to consist of an attitudinal and a behavioral component (Uncles, Dowling, and Hammond 2003).

Therefore, it is reasonable to expect that satisfaction and share of wallet are positively associated. This is supported by current marketing theory. In their model of customer asset management of services, Bolton, Lemon, and Verhoef (2004) propose that customer satisfaction has a positive influence on cross-buying, a proposition supported by several researchers (Anderson and Sullivan 1993; Cronin and Taylor 1992; Parasuraman, Zeithaml, and Berry 1988; Verhoef, Franses, and Hoekstra 2001; Zeithaml, Berry, and Parasuraman 1996); in other words, customer satisfaction is related to customers' allocation of a greater share of their spending to the firm.

In addition, Bowman and Narayandas (2004) and Keiningham, Aksoy, and colleagues (2005) conceptualize and operationalize the satisfaction–profit chain that Anderson and Mittal (2000) propose, which links satisfaction to retention as (1) satisfaction to (2) share of wallet to (3) revenue to (4) profit. The substitution of share of wallet for retention in the satisfaction–profit chain is further supported by Perkins-Munn and colleagues' (2005) research, which shows that the two constructs are highly correlated and that the relationship between attribute satisfaction and retention is similar to the relationship between attribute satisfaction and share of wallet.

Empirical research appears to confirm the link between satisfaction and share of wallet across various industries. Researchers have found a positive relationship between satisfaction and share of wallet for the fleet trucking (Perkins-Munn et al. 2005), pharmaceutical (Perkins-Munn et al. 2005), institutional securities (Keiningham, Perkins-Munn, et al. 2005), retail banking (Baumann, Burton, and Elliott 2005), processed metals (Bowman and Narayandas 2004), and grocery retailing (Mägi 2003; Silvestro and Cross 2000) industries. To date, however, research into the relationship between satisfaction and share of wallet has relied exclusively on cross-sectional data. Bernhardt, Donthu, and Kennett (2000, p. 164) also assert that "the true impact of satisfaction on performance measures is not apparent when taking a cross-sectional approach. A longitudinal view seems to be necessary."

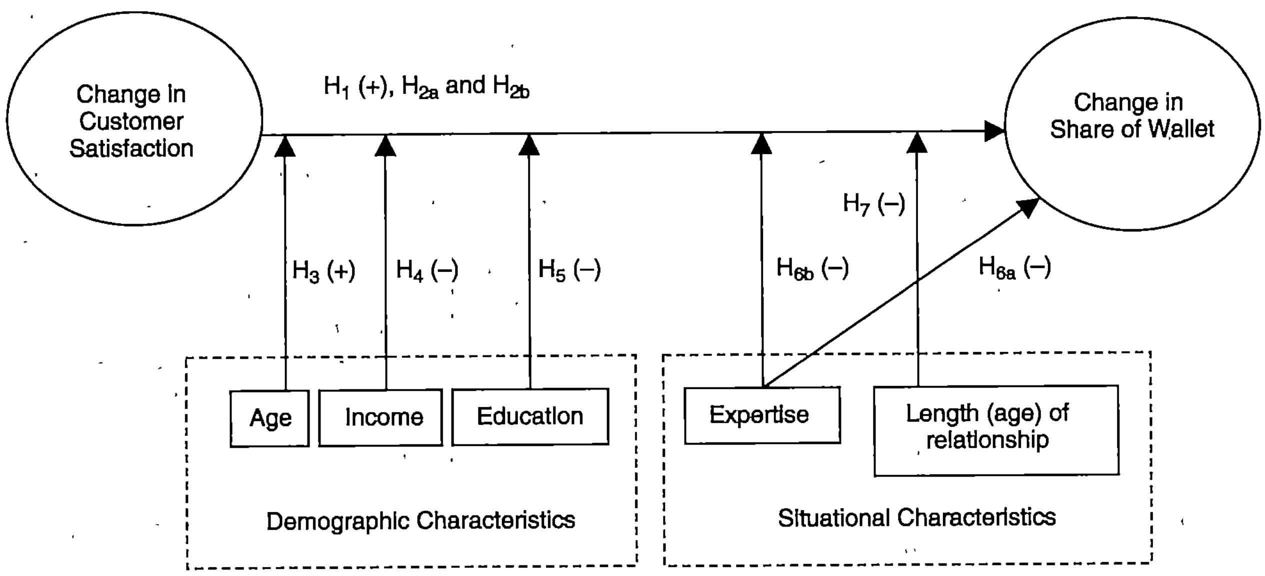
Although longitudinal examinations of the effect of customer satisfaction on other performance measures have found a positive relationship to customer retention (Bolton 1998), firm revenues (Bernhardt, Donthu, and Kennett 2000; Gruca and Rego 2005; Ittner and Larcker 1998), and shareholder value (Anderson, Fornell, and Mazvancheryl 2004; Fornell 2003; Fornell et al. 2006; Gruca and Rego 2005), the impact on share of wallet currently remains elusive.

Given the findings of cross-sectional studies regarding satisfaction and share of wallet and the findings of longitudinal studies regarding the relationship between satisfaction and other performance variables, we hypothesize the following (see Figure 1):

H_1: The relationship between a change in customer satisfaction and a contemporaneous change in current share of wallet is positive.

The effects of customer satisfaction on customer behavior and business results are widely believed to be nonlinear and asymmetric (Anderson and Mittal 2000; Coyne 1989; Jones and Sasser 1995; Keiningham and Vavra 2001; Oliva, Oliver, and MacMillan 1992). The nonlinearity and asymmetry of the relationship between customer satisfaction and repurchase intentions has been confirmed in several studies (Bloemer, Kasper, and Lemmink 1990; DeSarbo et al. 1994; Mittal and Baldasare 1996; Mittal et al. 1998; Oliver, Rust, and Varki 1997). Mittal and Kamakura (2001) find that this nonlinear and asymmetric relationship also holds true for repurchase. Likewise, Anderson (1998) finds that

FIGURE 1
The Model and Hypotheses


Change in Customer Satisfaction
H1 (+), H2a and H2b
Change in Share of Wallet
H7 (–)
H3 (+)
H4 (–)
H5 (–)
H6b (–)
H6a (–)
Age
Income
Education
Expertise
Length (age) of relationship
Demographic Characteristics
Situational Characteristics

the relationship between customer satisfaction and word of mouth is asymmetric and nonlinear.

Similarly, recent research on customer loyalty and share of wallet has uncovered nonlinear relationships. Austin and Singh (2005) report curvilinear effects of the determinants of loyalty intentions. Keiningham, Perkins-Munn, and Evans (2003) and Bowman and Narayandas (2004) find a positive, nonlinear relationship between satisfaction and share of wallet.

These findings can be explained, in part, through research on expectations. Satisfaction is "strongly influenced by customer expectations" (Rust, Zahorik, and Keiningham 1994, p. 42). Researchers have found multiple expectation thresholds. As expectations converge with respect to what is expected to happen, what should happen, and what would happen in the "ideal" situation, firms achieve greater competitive positioning (Boulding et al. 1993; Miller 1977; Swan and Combs 1976). This implies that there are expectation thresholds based on the consistency of delivery that must be met for customers to consider a firm.

The research on expectations interlocks well with the research of Kano (1997), Oliver (1997), and Anderson and Mittal (2000) regarding satisfaction. In particular, these researchers propose that there are thresholds with regard to performance of a particular attribute on customer satisfaction. Furthermore, Anderson and Mittal (2000) and Keiningham and Vavra (2001) propose that similar thresholds exist with regard to changes in customer satisfaction and changes in customer behavior (i.e., unless satisfaction levels reach a certain threshold, changes in satisfaction will have little impact on customer behavior). Early findings support such a relationship. In a longitudinal examination of customer satisfaction and sales performance for two retailers, Keiningham and colleagues (2006) find that the relationship between changes in satisfaction and changes in sales is determined, in part, by customers' baseline levels of satisfaction.

As a result, we do not expect that changes in share of wallet are linearly related to changes in satisfaction (as measured directly on a Likert scale). In particular, we expect that the baseline level of satisfaction affects the relationship between changes in satisfaction and changes in share of wallet.

Furthermore, the effect of satisfaction on share of wallet has been shown to differ by customer type (segment). Keiningham, Perkins-Munn, and Evans (2003) study the relationship between satisfaction and share of wallet, examining the impact of different organizational buyer groups. Their findings show that the relationship between satisfaction and share of wallet varies considerably by buyer group and that the relationship is nonlinear. Similarly, Baumann, Burton, and Elliott (2005) find that customer characteristics affect share-of-wallet allocations in retail banking; in particular, they find that age is positively associated with share of wallet. Thus:

> H_2: The positive relationship between changes in share of wallet and changes in satisfaction (a) depends on the baseline satisfaction level and (b) differs by customer segment.

Moderators in the Satisfaction–Share-of-Wallet Relationship

There is a stream of research that consistently finds variations in satisfaction ratings based on numerous customer characteristics (e.g., Bryant and Cha 1996; Mittal and Kamakura 2001; Peterson and Wilson 1992; Ross et al. 1999; Varki and Rust 1997; Venn and Fone 2005). Recently, it has been found that customer characteristics moderate the relationship between satisfaction and behavioral outcomes (Baumann, Burton, and Elliott 2005; Mägi 2003; Mittal and Kamakura 2001; Homburg and Giering 2001; Homburg, Giering, and Menon 2003; Keiningham, Perkins-Munn, and Evans 2003).

However, such analyses should not be limited solely to traditional demographic variables (e.g., age, education, income). Situational characteristics, such as price orientation (Kim, Srinivasan, and Wilcox 1999; Mägi 2003), tenure of relationship (Homburg, Giering, and Menon 2003), expertise (Andreassen and Lindestad 1998; Chiou, Droge, and Hanvanich 2002), involvement (Bloemer and Kasper 1995; Bloemer and Odekerken-Schröder 2002; Homburg and Giering 2001), and purchase volume (Mägi 2003), have all been found to influence the relationship between satisfaction and customer behavior. In this study, we investigate three demographic (age, income, and education) and two situational (expertise and tenure) variables. We specifically selected these variables because a stream of prior research has shown each to affect customer loyalty. A brief discussion of each of these potential moderators and their corresponding effects follows.

Age. Age moderates the relationship between satisfaction and loyalty (Baumann, Burton, and Elliott 2005; Homburg and Giering 2001). In particular, older consumers are more loyal to a particular brand than younger consumers in the automotive (Homburg and Giering 2001; Lambert-Pandraud, Laurent, and Lapersonne 2005) and banking (Baumann, Burton, and Elliott 2005) industries.

However, the expected relationship between age and loyalty has not been universal. A large-scale study by American Association of Retired Persons finds that older consumers are just as likely to switch brands or experiment with alternative brands as are younger consumers (Moos 2004). Mittal and Kamakura (2001) find that the relationship between satisfaction scores and repurchase behavior for cars is stronger for younger than for older consumers. Age has also been negatively linked to customer share (East et al. 1995; East et al. 2000). East and colleagues (2000) propose that older consumers have more free time, are able to spend more time shopping, and thus are able to shop at multiple stores. Some studies have found that the middle-age segment is the most loyal. Wright and Sparks (1999) find high loyalty in the 35–44 age group, and McGoldrick and Andre (1997) state that loyal shoppers are more likely to be the middle-age group. Conversely, Mägi (2003) finds that age does not moderate the relationship between satisfaction and loyalty for grocery consumers.

Despite contradictory findings regarding the impact of age, studies in the industry under examination, banking (see

Baumann, Burton, and Elliott 2005), suggest a positive impact. In addition, Lambert-Pandraud, Laurent, and Lapersonne (2005) apply four age-related theoretical perspectives to explain why age and loyalty should be positively associated: biological aging, cognitive decline, socioemotional selectivity, and change aversion. Applying this to the banking industry context, (1) biological aging suggests that increasing physical impairment associated with age reduces the number of banks customers use; (2) cognitive decline suggests that because of the reduced ability to evaluate complex options, older customers reduce their consideration set (i.e., number of banking relationships); (3) socioemotional selectivity suggests that older customers place a greater emphasis on feelings and emotions, and therefore, in the case of retail banking, older customers should be more interested in the relationship experience; and (4) change aversion is expected to increase with age, and therefore, in the context of banking, the risk older customers associate with switching banks is likely to be considered greater than it is for younger customers. Thus:

> H_3: The impact of a change in customer satisfaction on change in share of wallet increases with the consumer's age.

Income. A large body of research suggests that income is negatively linked to customer loyalty (Crask and Reynolds 1978; Korgaonkar, Lund, and Price 1985; Zeithaml 1985). Because higher-income consumers have fewer shopping restrictions, they are believed to exhibit less loyalty than low-income consumers (Sharir 1974; Zeithaml 1985). In addition, Homburg and Giering (2001) find that income is an important, negative moderator of the satisfaction–loyalty relationship.

However, findings regarding the relationship between income and customer behavior are not unanimous. In a study of online services, Keaveney and Parthasarathy (2001) find that online service "continuers" have higher average income levels than switchers. In the case of automobiles, Evans (1962) finds that fewer dealers are visited as incomes rise.

The discrepancy may be explained, in part, by customers' perceptions of the cost of time (Farley 1964a). A high-income consumer is believed to hold a higher valuation of time (Frank, Green, and Sieber 1967; Goldman and Johansson 1978; Marmorstein, Grewal, and Fishe 1992; Murthi and Srinivasan 1999). Therefore, a higher-income consumer may be more willing to trade off time in favor of a choice on the basis of limited evaluation, meaning that a consumer with a higher income may be less likely to evaluate in certain product categories. Indeed, there is empirical evidence that shows that income is negatively related to external search (Beatty and Smith 1987; Udell 1966).

Sharir (1974) argues that as households' cost of time increases, it affects customers' behavior in one of two ways: (1) Customers reduce their time spent buying goods (e.g., in search, deliberation, decision making), thus reducing consideration set size and increasing brand loyalty, or (2) customers avoid searching for information and deliberating on the brands to be bought, their sequence, and their shares and may buy at random (as with impulse buying), thus decreasing brand loyalty. Sharir argues that both patterns are likely to be relevant, but it is impossible to know a priori.

However, by its very nature, increased wealth provides greater opportunities to obtain a greater variety of financial products. Economic barriers affect the ability of lower-income and moderate-income households to hold various financial products (Barr 2004). In addition, customers' financial needs change as affluence increases (Asher 2001). Furthermore, several banking institutions compete primarily for high-income customers (Bielski 2004), whereas retail banking services are designed to have appeal across income levels.

Therefore, given that higher-income people have greater opportunities for more diverse financial products, that there is greater competition for their business, and that selection of financial products has a direct income-relevant component that may offset time costs, we hypothesize the following:

> H_4. The impact of a change in customer satisfaction on change in share of wallet decreases with the consumer's income level.

Education. Prior research tends to show that higher levels of education are associated with lower levels of customer loyalty (Chance and French 1972; Mittal and Kamakura 2001; Murphy 1978). People with higher education levels are believed to engage in greater information gathering and usage before decision making (Capon and Burke 1980). As a result, more highly educated consumers have greater awareness of alternatives. Furthermore, people with higher levels of education tend to be associated with higher income levels (Farley1964b), and as we noted previously, higher income can be associated with lower levels of loyalty. A notable exception has been found with regard to online services. As with the relationship between income and loyalty, however, Keaveney and Parthasarathy (2001) find that online service continuers have higher average education levels than switchers. Given that most previous studies have shown that higher levels of education are associated with lower levels of loyalty, we hypothesize the following:

> H_5: The impact of a change in customer satisfaction on change in share of wallet decreases as the consumer becomes more educated.

Expertise. Previous research shows that consumer expertise can influence customer loyalty (Bell, Auh, and Smalley 2005; Maheswaran 1994; Mitchell and Dacin 1996). East (1992) argues that higher levels of knowledge lead to lower levels of customer loyalty because knowledge provides customers with information about competing alternatives. Moorthy, Ratchford, and Talukdar (1997) argue that as customers gain experience, they use more attributes and more attribute levels to differentiate among offerings. This is likely due to the difference between novices' and experts' associative knowledge networks. Experts have more developed and complex cognitive structures than novices (Alba and Hutchinson 1987). As a result, experts may be more likely to be receptive to competitive offerings. Because novices find it more difficult to make comparisons, they perceive greater risk in decision making (Heilman, Bowman, and Wright 2000) and thus prefer to stay more loyal.

Capraro, Broniarczyk, and Srivastava (2003) conducted tests to determine whether knowledge mediates or moderates the satisfaction–customer retention linkage. However, their research supports neither mediation nor moderation, instead concluding that both knowledge and satisfaction independently influence customer defections. Given the preceding controversy, we propose the following alternate hypotheses:

> H_{6a}: Higher levels of expertise are negatively associated with a change in share of wallet, after the effects of other moderators are adjusted for.
>
> H_{6b}: The impact of a change in customer satisfaction on change in share of wallet decreases with higher levels of consumer expertise.

Length of relationship. Firm–customer relationships are evolutionary, time-adjusted associations. With repeated interactions, firms and customers develop bonds, and the reinforcements from satisfactory interactions help build customer loyalty (Anderson and Sullivan 1993; Anderson and Weitz 1989).

Customers with positive experiences over time are less likely to defect and are more forgiving (Anderson and Sullivan 1993). As a result, customers' judgments of recent exchange outcomes are influenced by the cumulative effect of long-term experiences with the product, service, or institution (Kalwani and Narayandas 1995). Thus, in the case of relationships that have aged, shifts in satisfaction have a weaker impact on loyalty. In addition, with time and effort investments, switching costs tend to increase, making it more difficult to switch.

Prior research tends to support this finding. Homburg, Giering, and Menon (2003) find that the longer the relationship between the buyer and the seller, the weaker the relationship is between customer satisfaction and customer loyalty. Thus:

> H_7: The impact of a change in customer satisfaction on change in share of wallet decreases with an increase in the length of relationship between the consumer and the company.

Methodology

Data Collection and Measurement

The data we used in this study were collected as part of an ongoing national panel study of Canadian bank customers for the years 2000–2004. More than 10,000 Canadian households are surveyed annually; information is gathered on all financial products (deposit, loan, and investment) and all financial institutions that each household used. Respondents are selected from across Canada, with representative sampling designed to mirror the geodemographic profile of Canadian households. When possible, respondents are tracked for multiple years. For the purpose of this investigation, we used only households that responded in two or more consecutive years.

This study provides sufficient information on 4319 households to test the seven hypotheses (16% for two years, 40% for three years, 23% for four years, and 21% for five years). For these households, there are 12,249 observations. Among the observed changes in share of wallet at each institution, 34% involve only "money-in" transactions (e.g., checking accounts, savings, investments), 1% involve only "money-out" transactions (e.g., loans, lines of credit, credit cards), and 65% involve both types of business (see Table 1). Share of wallet represents the percentage of total business, in dollars, conducted with the financial institution (e.g., total dollars with the institution divided by total dollars across all financial institutions; i.e., customers' relationships with all bank entities are recorded).

We measured overall satisfaction for the institution or institutions (up to three) that the respondent believed to be primary. We measured satisfaction on a four-point semantic scale (4 = "extremely satisfied," 3 = "somewhat satisfied," 2 = "somewhat dissatisfied," 1 = "extremely dissatisfied"). In addition, we included several customer characteristics in the study: age, income, education, length of relationship, and expertise. We did not measure expertise directly. Instead, we asked respondents if they used various professional financial advisory services. The use of such professional advisors could logically indicate (1) a degree of sophistication on the part of the customer and (2) direct access to subject-matter experts. It is reasonable to presume that use of financial advisors indicates a customer's desire to better manage his or her financial assets.

We recognize that a counterargument can be made about the use of a financial advisor. It might simply be a proxy for the respondent's lack of expertise. Although we believe that the former explanation is more probable than the latter, under either scenario, the use of a financial advisor would be construed as a proxy for expertise, the former being a positive association and the latter being a negative one. However, the variable we use here indicates only whether a customer used advisory services and provides

TABLE 1
Broad Breakdown of Types of Money-In and Money-Out Products Under Analysis

Money-In Products
- Checking and savings accounts
- Guaranteed investment certificates[a]
- Bonds[b]
- Stocks[b]
- Mutual funds[b]
- (Pensions are excluded)

Money-Out Products
- Credit cards
- Mortgages
- Personal loans
- Lines of credit (secured, unsecured)

[a] These are deposit investment securities sold by Canadian banks and trust companies. They are often bought for retirement plans because they provide a low-risk fixed rate of return. The principal is at risk only if the bank defaults.

[b] There is no Glass-Stegall equivalent in Canada to separate commercial banking from investment banking/securities brokerage

TABLE 2
Descriptive Statistics for 4319 Households and First Follow-Up

Variable Type	Variable	M	SD	First Quartile	Mdn	Third Quartile
Dependent						
	TB_SOW change (%)	0	28	–8	0	7
Satisfaction						
	Initial (category)	–	–	Satisfied	Extremely satisfied	Extremely satisfied
Moderators						
	Age (years)	53	15	42	53	65
	Income ($1,000 category)	–	–	25–30	45–55	70–100
	Education (category)	–	–	9–13 years	Some college	Certificate/diploma
	Tenure (years)	5.8	1.6	5.0	7.0	7.0
Business Activity						
	TB_SOW (%)	50	37	11	48	90
	Money-in ($1,000)	139.1	247.2	8.3	46.9	156.5
	Money-out ($1,000)	36.8	55.1	.00	9.6	62.5
	Money-out/TB (%)	32	47	0	0	100

Notes: Satisfaction decreased for 15% of first follow-ups (14% of all follow-ups); initial satisfaction was at either "satisfied" or "extremely satisfied" and did not move out of this range for 67% of first follow-ups (69% of all follow-ups). Additional information on other household characteristics at baseline: 78% sought professional advice, and 32% had only money-in accounts TB_SOW = total business share of wallet.

only limited information about customer expertise. Table 2 provides descriptive statistics on the 4319 households used in this study.

Model Development

We used a two-level latent class regression model to predict annual changes in the share of wallet per household with each financial institution. This model allows for household random effects, so that even though the data across households are assumed to be independent, the observations per household are independent only after conditioning on this random effect. This is a natural extension of the conventional approach, in that the probability of belonging to a given latent class is still a logistic function of covariates, but these covariates now include the household random effect (Vermunt 2003). This random effect has a mean of zero and a variance that is specific to the latent class. We estimated parameters with maximum likelihood estimation. The mathematical details appear in the Appendix. Lenk and DeSarbo (2000) also use random effects in a latent class framework, though their approach is mathematically and conceptually different.

To represent the change in satisfaction, we tested several candidate predictors, including the conditional percentile of change given the initial satisfaction level, the ordinal change in Likert scale units, indicators for any increase and any decrease, and indicators for whether a customer moved from a satisfied (Levels 3 or 4) to a dissatisfied (Levels 1 or 2) state and for any change in the other direction. Exploratory best-subsets analyses and preliminary restricted latent class model analysis indicated that the conditional percentile of change in satisfaction was the most important predictor and that other measures of change in satisfaction did not provide significant incremental value. The conditional percentile of change in satisfaction is the change in household satisfaction (from the original Likert scale) expressed as a conditional percentile relative to all other households that started at the same level of satisfaction.

Covariates for Latent Class

Preliminary latent class analyses showed that covariates representing the type and dollar level of household transactions from the last period were more important than household demographics for predicting total business share of wallet. Thus, we used the following covariates: the last period's values of (1) total business share of wallet (TB_SOW_{t-1}), (2) total dollar amount of money-in accounts (MI_{t-1}); (3) total dollar amount for money-out transactions (see Table 1) (money-out: MO_{t-1}), and (4) the proportion of total business in money-out transactions ($[\text{MO/TB}]_{t-1}$).

Predictors for Change in Total Business Share of Wallet

We used these same four variables as candidate predictors for total business share of wallet in the regression equations, along with an indicator for whether all business was in money-in transactions. Other candidate predictors included all the information about the moderating variables we proposed in H_3–H_7: household income, the length of time households used the services of the institution (tenure), whether they used financial advisory services (advisory), and the age and education of the head of the household who was taking the survey. We expressed household income and all education variables as percentiles relative to the sample. We measured brand effects by including indicators for the financial institution.

Model Selection

Initially, we included all information about transactions and household characteristics as predictors, along with the indicators for financial institution. We found the optimal number of latent classes by minimizing the Bayesian information criterion (BIC; Schwarz 1978; see also Bozdogan 1987). We chose BIC because it is a consistent criterion under general conditions (Rao and Wu 1989; Woodroofe 1982), and there is substantial theoretical and empirical work that suggests that it is effective in finding a good scientific model in many settings (Rust et al. 1995; Steyerberg et al. 2001), including latent class analyses (Biernacki and Govaert 1999; Dias 2004). We then modified the model by backward stepwise elimination of predictors and simplification across latent classes, in which the least significant predictors were removed (or refit with class independent coefficients when the difference in coefficient estimates across latent classes did not approach significance). At each step, we redetermined the corresponding optimal number of latent classes until there was no improvement in BIC (for additional details, see the Appendix). The final model also minimized the consistent Akaike information criterion (AIC) (Bozdogan 1987), but the analysis indicated that minimization of AIC (Akaike 1974) and AIC3 (Bozdogan 1994) would require much more complicated models (at least 17 latent classes).

Model Fit

Inferences made from linear latent class models are asymptotically valid under relatively general conditions and allow for considerable departures from normality (Satorra 2002). However, we also checked the validity of the model in several ways. Overall, the residual analyses and other model diagnostics indicate that there are no serious problems with model fit.

Residual diagnostics. In the final model, there is no significant serial correlation in the household residuals at Lag 1 and Lag 2 (in each case, $p > .3$). The nominal serial correlations indicate that less than one-tenth of 1% of the variance in residuals can be related to autocorrelation. This could be due to several factors, including the broad selection of candidate predictors, the differenced form of the dependent variable, and the model's facility (through segmentation and random effects) to accommodate longitudinal and cross-sectional heterogeneity effectively. We also tested stationarity over time by performing a one-way analysis of variance of residuals by year. The results indicate that there are no significant differences in average residual by year ($p = .63$), and this is true even when the analysis is restricted to residuals from annual changes in share of wallet that are two or more years from the household's baseline ($p = .71$). These analyses also support homoskedasticity of residuals across years. Finally, the plot of residuals versus predicted values does not suggest that there are any problems with the assumption that errors have a constant mean of zero across prediction levels.

Multicollinearity. For the coefficients that are related to H_1–H_7, the estimated variance inflation factors (VIFs) were always less than 2 across segments. The estimated VIFs for the structural coefficients of variables that describe account activity (TB_SOW_{t-1}, MI_{t-1}, and MO_{t-1}) are larger, presumably because these variables are also used as covariates for latent class membership. Even in this latter case, estimated VIFs do not exceed 3.5 (still substantially below the benchmark of 5, which is an indication of high multicollinearity).

Effect of extremes. We also calculated the Cook distance that corresponded to each residual. The distribution of these influence values is not significantly correlated with the size of the dependent variable (rank correlation = –.005, $p = .557$; raw correlation = –.001, $p = .882$), and the occurrence of a Cook distance >.5 (which happens only 2% of the time, less than expected in the classical case) is only marginally correlated with the absolute size of the dependent variable (rank correlation = .015, $p = .104$).

The Best Scientific Model

The model that minimized BIC is the 14-class model that Table 3 summarizes. Overall, it accounts for 95% of the change in total business share of wallet, but within the largest latent class (50% of households), the R-square is only 63%, the third lowest among all latent classes.

It is difficult to classify each case accurately into the appropriate latent class. A case represents an observed change in a household's total business share of wallet (along with the concomitant covariates and predictors for that household). The model makes classification errors with an estimated probability of 29.7%, and the proportional reduction in the entropy of classification is 70.2% when the model's posterior probabilities are used rather than the marginal probabilities of each latent class (Kamakura and Wedel 1995). For Class 1, the coefficient of the random-error effect (which has a mean of zero) is much larger than any of the other covariate effects, so the estimate that 50% of cases (and 50% of households) belong to this class is based primarily on the large estimated variance of the random effect.

These results indicate that, in many cases, it may be difficult to identify the most appropriate segment for an individual household. This is to be expected for a random effects model, and this uncertainty is a function of the natural heterogeneity among households. Reducing the number of segments can also improve these classification statistics, but such a reduction should be done only after fitting the best scientific model for segmentation, which typically includes segments that may be difficult to recognize. A manager should focus on the larger, more identifiable segments. Nevertheless, it is the more complex model, which may include managerially irrelevant segments, that provides the most accurate way of identifying segments for which targeted corporate efforts would be most profitable and the best framework for a rigorous examination of the hypotheses under study.

Profiles of the Primary Latent Classes

Table 3 describes the profiles in terms of the dependent variable, change in TB_SOW (change between times t and t – 1), the contemporaneous change in satisfaction, and other variables measured in initial period (t – 1). As Table 3 shows, the first two latent classes are similar to each other and unique among the 14 customer segments in several ways:

TABLE 3
The Best Scientific Model: Class Sizes, R-Square, and Latent Class Profiles Averages

Class	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Overall
R^2	63	100	81	65	96	41	25	65	100	98	95	100	66	98	95
Percentage of cases	50.0	12.1	5.0	4.8	4.7	4.4	3.5	3.3	2.9	2.7	2.3	1.9	1.9	.5	100
Percentage of household types	50.0	18.1	2.3	4.4	2.8	5.8	5.6	1.2	4.3	1.1	.9	.8	2.6	.2	100
Change in TB_SOW ($\%SOW_t - \%SOW_{t-1}$)	25	20	–13	0	–29	0	2	–2	–35	18	–7	18	0	2	2
Initial satisfaction (1–4, 4 is the highest)	3.5	3.6	3.4	3.3	3.4	3.2	3.4	3.4	3.4	3.5	3.3	3.5	3.5	3.4	3.4
Change in satisfaction (Conditional percentile, %)	51	52	50	48	48	48	50	50	48	51	49	51	52	50	50
Percentage with SAT = 3 or 4 and no change	72	72	70	66	66	60	70	70	66	70	67	69	70	66	68
Percentage for whom satisfaction decreased	14	13	14	15	17	16	14	14	18	13	15	15	13	15	15
Percentage for whom satisfaction increased	14	13	15	17	15	20	14	15	14	15	16	15	15	17	15
Age (years)	50	57	56	56	56	56	56	56	56	53	54	52	51	52	55
Income (percentile, %)	54	36	43	59	47	54	63	56	44	48	53	50	58	54	50
Education (percentile, %)	51	43	48	53	49	55	55	52	47	48	51	49	50	51	50
Sought professional advice (%)	88	87	85	89	85	89	88	86	87	87	87	87	89	87	87
Length of relationship (years)	5.8	6.1	6.0	6.0	5.9	5.8	5.9	5.9	5.8	5.8	5.8	5.9	5.9	5.9	5.9
Initial TB_SOW (%)	76	84	52	11	38	1	45	46	32	72	11	80	94	44	50
Money-out ($1,000)	51	20	17	48	18	48	56	42	21	37	41	47	72	40	36
Money-in ($1,000)	100	69	70	262	110	285	312	163	99	86	148	84	210	149	147
Percentage with only money-in	21	48	38	31	40	32	32	33	36	27	29	20	23	21	34
(Money-out/Total-business) × 100%	45	28	29	31	26	35	29	30	34	40	32	48	46	45	33

Notes: Change in TB_SOW is the dependent variable; the predictors are in bold, and other variables are in italics; change in TB_SOW and change in satisfaction are contemporaneous; and all other variables are measured at the initial period (time t – 1). In the case of the variable "percentage with only money-in," we used an indicator to indicate when all household accounts were money-in (at baseline). An average change in satisfaction at the 51st conditional percentile indicates that, on average, these households had a change in satisfaction that was better than or equal to that of 51% of the households that started out at the same satisfaction level.

- They are the largest segments (Class 1: 50% of cases and households; Class 2: 12% of observations and 18% of households);
- They have high initial satisfaction (Class 1 is the third highest, and Class 2 is the highest): extremely satisfied = 56% and 60% for Classes 1 and 2, respectively, and somewhat satisfied = 39% and 31%, respectively;
- They remain at high levels of satisfaction: In each class, 72% of households were initially at one of the two highest levels of satisfaction and remained at precisely the same level during the next period (this is the highest level of high unchanged satisfaction among all classes); and
- They have large average values of total business share of wallet with a primary institution: 76% and 84% for Classes 1 and 2, respectively.

However, the two largest classes also differ dramatically in terms of demographic characteristics and the type of business they conduct with their primary institutions:

- Class 1 has the lowest average age (50), and Class 2 has the highest average age (57);
- In Class 1, education is slightly above average (64% with some college), and Class 2 has the lowest average education (51% with some college);
- In Class 1, the average income is slightly above the median (54th percentile); and Class 2 has the lowest average among all classes (36th percentile);
- In Class 1, the tenure of the relationship with the primary institution is just below the average among all classes (5.8 years), and Class 2 has the longest average tenure among classes (6.1 years); and
- Class 1 has the largest percentage of total business in the money-out category among classes, representing more than 1% of households (45% money-out), and Class 2 has the second-lowest percentage of money-out business among all classes (28%).

Predictor Significance in the Latent Class Regressions

Three covariates used to determine the latent class were also of preeminent importance as predictors (TB_SOW_{t-1}, MI_{t-1}, and MO_{t-1}), along with the indicator for whether all household transactions (of the last period) were money-in. As Table 4 shows, the other important predictors were income, tenure, the conditional percentile of change in satisfaction, and the initial satisfaction level. Tested across all classes, all predictors have significantly nonzero coefficients ($p < .0001$) that are also significantly different across classes ($p < .0001$). Brand (the actual financial institution) did not have any significant incremental value for predicting the change in total business share of wallet, and therefore we did not include it in these models. In this discussion of predictor effects, we refer to the actual average change in total business share of wallet ($TB\_SOW_t - TB\_SOW_{t-1}$) in which each term is expressed as a percentage. This is the difference between successive values of share of wallet, so even though it is also expressed in units of percent, it does not actually represent the percentage change in share of wallet relative to the actual baseline level of share of wallet.

Effects of Last Period's Business Type and Dollar Amount

The last period's total business share of wallet (TB_SOW_{t-1}) has a negative coefficient in every class, indicating that, on average, customers tend to make smaller positive or even negative adjustments to TB_SOW when it is already at higher levels, all else being equal. In contrast, the dollar level for money-in and money-out can have either a positive or a negative impact, depending on the latent class, but it always has an impact of less than .1% on total business share of wallet per thousand dollar increase in level. Similarly, the coefficient of the indicator for whether all business consists of money-in transactions can also be negative or positive. The largest coefficient estimate is in the largest latent class (Class 1), but even here, the effect is an average reduction of only 2% in the in total business share of wallet for households in which all transactions are money-in relative to households in which there is also money-out business. Nevertheless, the coefficients of these predictors (and the others we discuss subsequently) are highly significant and significantly different across classes (for both tests on each predictor, $p < .0001$).

TABLE 4
Latent Class Regression Coefficients for Predictors Representing Satisfaction and Satisfaction Moderators in Classes That Represent at Least 4% of Either Cases or Household Types

	1	2	3	4	5	6	7	9
Class								
R^2	63	100	81	65	96	41	25	100
Percentage of cases	50	12	5	5	5	4	4	3
Percentage of household types	50	18	2	4	3	6	6	4
Predictor Coefficients								
Initial satisfaction (1–4, 4 is the highest)	2.0	.0	.9	1.0	.9	.1	–.1	.0
Change in satisfaction (50% change in conditional percentile)	2.7	.0	5.1	.6	2.1	.1	.8	.0
Income (percentile, %)	–2.9	–.0	–10.1	–1.0	.5	.1	–2.0	.4
Length of relationship (years)	–.2	.0	.6	–.3	.6	.0	.5	–.0

Notes: Each coefficient represents change in TB_SOW ($\%SOW_t - \%SOW_{t-1}$) per unit change in predictor, all else being equal For change in conditional percentile of satisfaction, one unit change in this predictor represents a comparison between the third and the first quartiles of the distribution of annual changes in satisfaction among households that started at the same satisfaction level. All coefficients are significantly nonzero and significantly different across classes (for each test, $p < .0001$).

Results

The Effect of Change in Satisfaction (H_1 and H_2)

Remarkably, among all the predictors, only the conditional percentile of change in satisfaction has a nearly consistent positive coefficient in each regression (Table 4), in support of H_1. The only exception is Class 11 (not shown in Table 4), which represents approximately 2% of the observed changes in profiles and represents less than 1% of all households; yet even in this case, it is not significantly negative (the one-sided p value is .45), representing less than one-tenth of 1% average change in total business share of wallet, even for households that undergo the highest possible percentile of change in satisfaction. In the largest latent class (50% of observations and households), total business share of wallet increases by an average of 2.7% per 50-percentile increase in satisfaction (relative to customers who started at the same satisfaction level). Nevertheless, as Table 4 shows, among the other latent classes that each represent at least 4% of households (Classes 2, 4, 6, and 7), the increases in total business share of wallet are less than 1% per 50-percentile increase in satisfaction, and with the exception of Class 1, the average increase per household is only .3% per 50-percentile increase in satisfaction. These changes assume that adjustments for other household characteristics (e.g., type and level of business, tenure, income, and initial satisfaction level) have been made.

These results confirm a significant and positive, though somewhat modest, relationship between change in satisfaction and the concomitant change in total business share of wallet. This relationship differs by latent class and baseline satisfaction level, but it is strongest in the largest class (50% of households). Among the four classes that represent at least 4% of households, the largest class is characterized by the second-largest average volume of money-out business ($51,000) and the largest proportion (45%) of money-out dollars as a proportion of total business; thus, these are the types of customers who generate a large share of a financial institution's profits.

After correcting for other variables in the model, including the initial satisfaction level, the best model posits a linear relationship per unit change in conditional percentile within latent class. However, this is not a linear relationship relative to the Likert scale, and it is not a constant linear relationship in percentile units across latent classes ($p <$ .0001). Furthermore, this within-class relationship requires an adjustment for initial satisfaction level. Because satisfaction is not measured on a ratio scale, its coefficient is interpreted as the parameter needed to calculate a new intercept on the basis of initial satisfaction ([original segment intercept + segment coefficient] × [baseline satisfaction on the Likert scale]), which changes by segment. In this way, it represents a segment-specific coefficient that provides a new anchor point for how share of wallet changes with each baseline satisfaction level, and this adjustment changes in an approximately linear way relative to the Likert scale (after we correct for change in satisfaction on a conditional percentile scale and for other moderating and structural variables).

In the largest latent class and in all other classes except three (of which only Class 7 is large enough to be in Table 4), total business share of wallet also increases per increased level of initial satisfaction. These adjustments are modest (always less than 4% per Likert point). In the largest latent class, the coefficient represents an average increase of 2% per Likert point. In summary, the results are consistent with H_2; we find a positive relationship between changes in share of wallet and changes in satisfaction that differs by customer segment and also depends on the baseline satisfaction level.

Moderators for the Effects of Change in Satisfaction (H_3–H_7)

We tested the variables referred to in the seven hypotheses for incremental value in the model. Initially, we considered all these variables candidates, and we eliminated each in turn only if a better scientific model (lower BIC) could be obtained by doing so. In each case, we tested the effects of each variable after correcting for the effects of the other variables that are in the final (best scientific) model.

H_3. Overall, there is no evidence that age is a positive moderator. The age of the head of the household does not seem to have any significant incremental value (p = .18). Among the four largest latent classes (Classes 1, 2, 6, and 7, representing 50%, 18%, 6%, and 6% of households, respectively), change in satisfaction has the strongest effect in Class 1, in which the head of the household tends to be an average of at least five years younger. Thus, H_3 is not supported.

H_4. Income is an important predictor in the final model and thus is significant and significantly different across classes (in both cases, $p <$ .0001). It has a negative coefficient in 9 of the 14 latent classes, and these 9 classes represent 86% of all households. Its effects, however, are modest. Its largest negative impact is in Class 1, in which there is a 1.7% average decrease in total business share of wallet per 50-percentile increase in income, conditional on fixed levels of change in satisfaction and other household characteristics. These results support H_4, that income tends to moderate the relationship between changes in satisfaction and changes in total business share of wallet negatively.

H_5. Education is not a predictor in the best model and does not have significant incremental value in this model (p = .74). There is a high correlation between income and education (r = .987, $p <$ .0001, in which both variables are measured in terms of percentiles), so it can be used as a proxy for income; as such, it would be a negative moderator (as H_5 posited), but income seems to be more directly related to changes in total business share of wallet.

H_6. The indicator for whether financial advisory services were used was not in the final model and did not have any incremental value when we added it (p = .29). Therefore, there is no support for H_6 regarding the effects of expertise. However, the variable we used here indicates only whether a customer used advisory services and provides only limited and hypothetical information about the actual moderating effects of customer expertise.

H_7. Length of relationship (tenure) with the financial institution was a significant predictor in the final model and had significantly different effects across classes (in both tests, $p < .0001$). Its coefficient is negative in Class 1, in which there is an average decrease of .2% in total business share of wallet per year of tenure. It is never greater than its value in Class 3, which represents 2% of households and in which there is an average increase of .6% in total business share of wallet per year. Thus, its overall effect is modest; the average effect per household is –.08% per year. The coefficient is negative in only 4 of the 14 latent classes, but these 4 classes represent 60% of households. Thus, there is strong empirical support for the significance of this variable, and though its effects are modest, it tends to be a negative moderator (as hypothesized).

General Discussion and Conclusions

Our analysis advances the empirical research on the intuitive relationship between customer satisfaction and business outcomes in two key ways. First, our findings indicate that changes in satisfaction are positively and nonlinearly related to the share of wallet a customer allocates to a particular service provider over time; specifically, the initial satisfaction level and the conditional percentile of change in satisfaction significantly correspond to changes in share of wallet.

Second, the findings suggest that the relationship between satisfaction and share of wallet is moderated by both demographic and situational customer characteristics. In particular, income and length of relationship are significant predictors in the model. Both income and length of relationship negatively moderated the relationship between changes in satisfaction and share of wallet. This corresponds to similar findings regarding the relationships between satisfaction and repurchase intention and between satisfaction and retention (Mittal and Kamakura 2001).

The key implication is that managers should not simply strive to improve reported satisfaction levels without an understanding of the relationship to customers' share-of-wallet allocations. Given that both the initial satisfaction level and the conditional percentile of change in satisfaction are significantly associated with changes in share of wallet, it is critical that managers design their efforts to improve satisfaction so that customers reach the satisfaction levels that correspond to higher share-of-wallet levels. This may require a reevaluation of the means with which managers currently measure the potential return on investment from improvement efforts aimed at changing customer behavior through improved customer satisfaction, particularly if cross-sectional analyses are currently used. Cross-sectional (as opposed to longitudinal) examinations of the relationship between customer satisfaction and customer behavior may be unable to identify adequately the roles of both baseline satisfaction levels and change in satisfaction on customers' share-of-wallet allocations.

Furthermore, simply treating all customers as homogeneous has the potential to misrepresent the relationship between satisfaction and share of wallet. Therefore, it is important that the level of influence of various customer segments on share of wallet be uncovered so that resources can be appropriately allocated to those areas, thus providing the greatest impact. For example, in this study, there is an interesting contrast between the households in the two largest classes; households in Class 1 tend to be clients with more income and a larger volume of money-out business than clients in Class 2, and they are also more responsive to both higher baseline satisfaction levels and positive changes in satisfaction.

The influence of satisfaction on customers' share-of-wallet allocations to a bank has strategic implications for managers. As opposed to retention (i.e., the business relationship is on/off), the ability to manipulate share of wallet demonstrates that many, if not most, customers have relationships with multiple financial institutions rather than an exclusive/monogamous relationship with an individual institution. Therefore, customers are more likely to be aware of competitors' offerings and to have some level of interaction with competing institutions. Knowledge and experience lower customers' perceived risk (Rust, Zahorik, and Keiningham 1994). Consequently, changes in service levels that affect the level of customer satisfaction can more easily result in the inflow or outflow of money to the firm. Given the increasingly polygamous loyalty that consumers hold toward firms/brands (Bennett and Rundle-Thiele 2005; Rust, Lemon, and Zeithaml 2004; Uncles, Dowling, and Hammond 2003; Uncles, Ehrenberg, and Hammond 1995), this issue is likely to transcend the banking industry.

Limitations and Further Research

This study used data from a business-to-consumer relationship within a single industry. As such, the results cannot be immediately applied to different industries or to business-to-business relationships. Similarly, this study focuses exclusively on the relationship between overall satisfaction levels and share of wallet. More comprehensive models that account for the relationship between attribute-level satisfaction and share of wallet could provide managers with important insights into more tactical measures that firms could take to improve the percentage of business their customers give to them versus to their competition.

In addition, this article investigated the moderating influence of three demographic (age, income, and education) and two situational (expertise and tenure) customer characteristics variables. However, firms use a host of customer characteristics to segment their customer bases. In many cases, our findings differed from those previously hypothesized in or logically inferred from prior research. Finally, our analysis identified the presence of a statistically significant relationship only between changes in share of wallet and concomitant changes in satisfaction, along with the statistically significant and insignificant effects of moderating variables. We did not prove causation. Therefore, to examine the robustness of these findings, additional research should be conducted regarding both the longitudinal relationship between satisfaction and share of wallet and the moderating influence across several customer characteristics in various industries and countries.

Appendix

We modeled the change in total business share of wallet with a two-level latent class regression across J groups (J = 4319 households) and K latent classes. Here, y_{ij} represents the ith observed change in total business share of wallet at household j (i = 1, …, n_j). The log-likelihood is

$$\text{(A1)}\qquad \log L = \sum_{j=1}^{J} \log \int_{\xi_j} \left[\prod_{i=1}^{n_j} f(y_{ij} | Z_{ij}^{cov}, Z_{ij}^{pred}, \xi_j, \Theta) \right] f(\xi_j) d(\xi_j),$$

where the parameters, Θ, include the covariate parameters, Γ, used in the logistic model for the latent classes and regression coefficients $\mathbf{B} = (\beta^{(1)}, \ldots, \beta^{(K)})$, where $\beta^{(k)}$ is the vector of coefficients used in the regression model for y_{ij} within latent class k, k = 1, …, K. In Equation A1, the integration is with respect to the vector of random effects $\xi = (\xi_1, \ldots, \xi_J)$, which, as we show subsequently, accommodates differences among the J households. Let X_{ij} represent the latent class variable so that $P(X_{ij} = k)$ is the probability that observation i from household j belongs to latent class k. Then, the K latent class density for y_{ij}, which is referred to in Equation A1, is

$$\text{(A2)}\qquad f(y_{ij} | Z_{ij}^{cov}, Z_{ij}^{pred}, \xi_j, \Theta) = \sum_{k=1}^{K} P(X_{ij} = k | Z_{ij}^{cov}, \xi_j, \Gamma) f_k(y_{ij} | Z_{ij}^{(pred,k)}, \beta^{(k)}, \sigma_k),$$

where, for latent class k, (1) the density, f_k, of y_{ij} is a normal distribution with variance σ_k^2 and a mean μ_k that is a linear function of the S_k predictors $Z_{ij}^{(pred,k)} = (z_{ij1}^{(pred,k)}, \ldots, z_{ijS_k}^{(pred,k)})$ used in class k (which are a subset of the matrix of all predictors, Z_{ij}^{pred}, used in the model), with coefficients $\beta^{(k)} = (\beta_0^{(k)}, \beta_1^{(k)}, \ldots, \beta_{S_k}^{(k)})$,

$$\text{(A3)}\qquad \mu_k = \beta_0^{(k)} + \sum_{r=1}^{S_k} \beta_r^{(k)} z_{ijr}^{(pred,k)},$$

and (2) $P(X_{ij} = k | Z_{ij}^{cov}, \xi_j, \Gamma)$ is the logistic probability that observation i from household j is in latent class k,

$$\text{(A4)}\qquad P(X_{ij} = k | Z_{ij}^{cov}, \xi_j, \Gamma) = \frac{\exp[\eta(k | Z_{ij}^{cov}, \xi_j)]}{\sum_{\ell=1}^{K} \exp[(\eta(\ell | Z_{ij}^{cov}, \xi_j)]},$$

where

$$\text{(A5)}\qquad \eta(\ell | Z_{ij}^{cov}, \xi_j) = \gamma_{\ell 0} + \sum_{r=1}^{R} \gamma_{\ell r} z_{ijr}^{cov} + \gamma_{\ell 00} \xi_j,$$

for ℓ = 1, …, K. In Equations A4 and A5, the ξ_j, j = 1, …, J, are assumed to be independent standard normal random effects, which is not restrictive given the flexibility that is provided in Equation A5 by the random effect coefficients, $\gamma_{\ell 00}$, which correspond to each latent class ℓ, ℓ = 1, …, K, and are subject to the identifiability constraint $\Sigma_{\ell=1}^{K} \gamma_{\ell 00} = 0$.

Departures from Normality

Statistical inferences based on normality have been shown to remain valid and even asymptotically efficient under general conditions that permit substantial departures from normality, even in the case of latent class models (Satorra 2002). In this case, the validity of inferences under nonnormality is even less of an issue because of the bounded nature of the dependent variable (because Huber's condition on the projection matrices is satisfied; see Arnold 1981, Chap. 4; Huber 1980, pp. 155–60). Inferences are subject to the correct specification of the linear model and require random error, which is also homoskedastic within each class, but the diagnostics we discussed previously (see the "Model Fit" subsection) provide substantial empirical evidence that these assumptions are met.

Model Selection Procedure

Preliminary latent class analyses indicated that four variables (the last period's values of TB_SOW_{t-1}, MI_{t-1}, MO_{t-1}, and $[MO/TB]_{t-1}$), all of which describe the account activity at baseline, were important and natural covariates for determining the latent class. These covariates were highly significant in all multiple latent class models. In addition, we included all information on transactions and household characteristics, along with the indicators for financial institution, as predictors (for the dependent variable, change in TB_SOW) in the initial model. Given this selection of covariates and the preliminary selection of all candidate predictors, we found the optimal number of latent classes by minimizing the BIC (Schwarz 1978; see also Bozdogan 1987). We then modified the model with a backward stepwise procedure in which, at each step, we experimented with (1) the elimination of the predictor that was least significantly nonzero (according to a joint Wald test for whether it was significantly nonzero in any class) and (2) the simplification of predictors by fitting them with class-independent coefficients (when the coefficient estimate were not significantly different across classes). When we eliminated predictors, it was necessary to redetermine the optimal number of classes, but ultimately we made these modifications only if BIC improved. In a final stage of the analysis, we retried a forward step with each predictor that had been eliminated to determine whether a better model was possible. In the final model, all predictors have coefficients that differ by latent class.

Stepwise procedures do not always lead to global optima. The optimal subset of covariates and predictors typically depend on the number of latent classes modeled. It might be considered ideal to perform a best-subsets analysis for each plausible selection of the number of classes and then choose the best model from among those solutions. Nevertheless, our own search indicates that the optimal number of classes changes only slightly, if at all, as the set of covariates and predictors change.

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Gangseog Ryu & Lawrence Feick

A Penny for Your Thoughts: Referral Reward Programs and Referral Likelihood

Because referral reward programs reward existing customers and build the customer base, firms use them to encourage customers to make recommendations to others. The authors report on four experiments in which they find that rewards increase referral likelihood. More specifically, they find that rewards are particularly effective in increasing referral to weak ties and for weaker brands. It is also important who receives the reward. Overall, for weak ties and weaker brands, giving a reward to the provider of the recommendation is important. For strong ties and stronger brands, providing at least some of the reward to the receiver of the referral seems to be more effective. The authors discuss the implications of the results for the design of reward programs.

Word of mouth (WOM), at one time viewed as a sociological phenomenon to be observed and described, is increasingly considered a marketing tool to be managed (Rosen 2000). In initial efforts to manage WOM, marketers focused on satisfying customers (so that they would generate positive rather than negative WOM) and on targeting influential consumers, such as opinion leaders. Only recently have firms introduced formal programs that are designed to encourage existing customers to make product recommendations. In these programs, firms offer various types of rewards (e.g., vouchers, gifts, free minutes, miles) when an existing customer attracts a new customer. Such programs have significant potential to affect firms' performance. For example, consider customer relationship management (CRM), recently a central focus of marketers' attention (Hogan, Lemon, and Libai 2003; Rust, Lemon, and Zeithaml 2004). A core idea in CRM is that firms need to invest in retaining existing customers not just in finding new ones. Thus, a referral reward program can be a key CRM tool because in addition to its potential to attract new customers, it can improve retention by rewarding existing customers.

A review of Web search results suggests that the practice of rewarded referral is widespread. Referral reward programs exist for a wide variety of goods (e.g., contact lenses [Smart View Contacts], automobiles [Hanmar Motors], pet supplies [Neo-Paws]) and services (e.g., airlines [United Airlines], mobile phone service [Cingular]). They provide rewards that can be discounts on the product or service (e.g., discounted future hotel stays [Caesar's Pocono Resort], free perfume [Perfumeoutlet.net]) or cash and gifts unrelated to the product or service category being recommended (e.g., car dealers [#1 Cochran], real estate agencies [REMAX]). Researchers expect an increasing use of such programs because of their targetability and cost effectiveness compared with more traditional promotional tools (Mummert 2000).

However, there is limited research on rewarded referral. Some scholars have examined the impact of various marketing activities on WOM. For example, Bolton, Kannan, and Bramlett (2000) show that offering a loyalty program has an indirect effect on customers' repatronage behavior and on their WOM. Blodgett, Hill, and Tax (1997) find that the way customers are treated has a greater impact on complaining customers' negative WOM intention than does offering discounts. Apart from these indirect approaches to studying the effects of offering rewards on WOM, two recent analytical studies offer guidance for developing optimal referral reward programs. First, on the basis of the premise that customers make recommendations when they are delighted, Biyalogorsky, Gerstner, and Libai (2000) identify conditions under which a referral reward program is more effective than a price reduction in enhancing the firm's profitability. Second, Chen and Shi (2001) use game theory to demonstrate that the optimal referral reward (cash versus free products) varies according to market structure (monopoly versus oligopoly). Overall, however, there has been almost no empirical work.

This article reports the results of four laboratory experiments that investigate the impact of referral reward programs on referral likelihood. Across our studies, we examine the effect of the presence or absence of a reward, reward size, and reward recipient (i.e., does the existing customer,

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does the new customer, or do both get the reward?). We also examine the impact of the relationship between the recommender and the receiver of the recommendation (i.e., strong or weak ties) and of brand strength (i.e., stronger or weaker brands). Our results have implications for the design of reward programs and for WOM theory.

Conceptual Background

We adopt an exchange theory framework for examining consumers' responses to referral reward programs. From this perspective, the customer's decision about whether to engage in WOM depends on the perceived costs and benefits of the exchange (Frenzen and Nakamoto 1993; Gatignon and Robertson 1986; Walster, Walster, and Berscheid 1978). Research on WOM identifies several (primarily psychological or social) benefits of or motivations for transmitting WOM (Arndt 1967; Dichter 1966; Gatignon and Robertson 1986). For example, consumers may use WOM in an attempt to reduce postpurchase anxiety or dissonance by talking about their product experiences. In addition, consumers may use WOM as a way to manage others' impressions of them. Finally, WOM can be a means of expressing concern about others and helping them make better choices. Providing WOM also involves costs (Gatignon and Robertson 1986). The most obvious cost is the effort and time spent communicating. In addition, because of the norm of reciprocity, the recommender may feel obliged to be a "good listener" in future communication. Finally, there is the risk that if the receiver is dissatisfied with a purchase that results from the recommendation, the relationship will suffer (Folkes 1984).

With referral reward programs, exchange is more complex. As with natural WOM, there is the communication between the recommender and the receiver of a referral. If the referral successfully leads the receiver to purchase the product, another exchange will take place between the receiver and the company. Finally, the recommender receives a reward from the company in return for the referral. Because obtaining the reward is a result of the purchase, the receiver (new customer) provides a benefit (albeit indirectly) to the recommender (existing customer).

We expect that this added exchange complexity affects how consumers perceive a referral's costs and benefits. The obvious additional benefit is the (economic) gain from the referral. On the cost side, if the receiver of the rewarded referral is dissatisfied with the product, there is increased (social) risk that the receiver might attribute his or her dissatisfaction to the recommender. Self-perception theory (Bem 1965, 1972) suggests that people try to understand the causes of their own behavior. If a referral is rewarded, consumers may perceive the referral as being driven by the reward rather than by intrinsic motivations. As a result, recommenders may feel as if they "sold" their recommendation, a perception unlikely to be consistent with their self-image.

For a firm to consider a referral reward program effective, the program should show results beyond what would occur naturally. In other words, the marginal gain from the reward program should be large enough to compensate for its cost. Thus, natural WOM is the appropriate comparison in the evaluation of the effects of referral reward programs.

Study 1

In Study 1, we investigate whether the presence or absence of a reward and reward size influence satisfied customers' referral likelihood. In addition, we examine the moderating effects of strong versus weak ties between the recommender and the receiver and of the strength of the brand offering the reward.

Referral Rewards and Tie Strength

Unlike more traditional sales promotion and customer loyalty programs that involve only the customer and company, referral reward programs also have implications for other consumers. Consumers consider the value of potential gains and costs for themselves and for the other consumer in rewarded referral. The nature of the recommender–receiver relationship influences these perceptions of costs and benefits. Research shows that tie strength is an important property of relationships in determining how social context affects referral (Brown and Reingen 1987; Reingen and Kernan 1986). Tie strength varies from strong primary, such as spouse or close friends, to weak secondary, such as seldom-contacted acquaintances (Reingen and Kernan 1986).

With strong ties, people tend to have communal relationships in which they feel general concern about the other person's welfare. They respond to the other's needs but do not expect anything in return (Clark 1984; Clark, Mills, and Powell 1986; Frenzen and Nakamoto 1993). Conversely, with weak ties, people typically have exchange relationships, driven primarily by self-interest. In such relationships, participants do not feel any special responsibility for the other person and try to maximize their own outcomes and minimize their costs. With weak ties, reciprocity is important; people expect to get back what they put in. People prefer an equitable (balanced) exchange, and if it is unbalanced, they feel distress and try to adjust. In such cases, they try to reduce what they give or increase what they receive to achieve equilibrium (Walster, Berscheid, and Walster 1973; Walster, Walster, and Berscheid 1978).

Research on naturally occurring WOM finds that consumers are more likely to make a referral to a strong tie than to a weak tie (e.g., Brown and Reingen 1987; Frenzen and Nakamoto 1993), perhaps because their communal orientation toward strong ties motivates them to share the pleasure that they have received from using a product. Furthermore, people know much more about the needs and preferences of strong ties because they are in frequent contact with them (Granovetter 1973) and keep track of their needs (Clark, Mills, and Powell 1986). Greater knowledge about preferences is likely to make consumers feel more comfortable about sharing experiences and make the information more useful, especially for products from high-preference-heterogeneity categories (Feick and Higie 1992).

What changes are expected when a reward is offered for a referral? We consider strong ties. On the benefit side, a reward should have little additional impact. Consumers help without expecting a reward; indeed, helping is its own reward (Beach and Carter 1976; Clark, Mills, and Powell 1986). Frenzen and Nakamoto (1993) find that consumers are likely to share all types of information with strong ties (including both high- and low-value information). On the cost side, there is the potential social risk of negatively affecting a relationship if an economically driven referral does not work out. Thus, with strong ties, because the marginal benefit is small and because of potential (social) costs, we expect little impact of a reward on referral likelihood.

In contrast, for weak ties, equity theory suggests that a recommender will regard a referral as a favor done for the receiver and/or the company. Thus, referrals yield inequity because an input is increased without a simultaneous increase in output (Walster, Berscheid, and Walster 1973; Walster, Walster, and Berscheid 1978). If the recommender receives a reward, the level of inequity is reduced, resulting in movement toward equilibrium. Furthermore, unless the economic value of the reward is large, it seems unlikely that a concern about "being bought" will be important to the recommender in interacting with a weak tie. Thus, with weak ties (in exchange relationships), we expect that consumers will be more influenced by economic motives and less concerned about the social or psychological risks of rewarded referral (Frenzen and Nakamoto 1993; Törnblom and Nilsson 1993). Thus:

> H_1: The impact of offering a reward on referral likelihood depends on tie strength. The presence of a reward (compared with no reward) increases referral likelihood more for weak ties than for strong ties.

Referral Rewards and Brand Strength

Brand features also should moderate the effect of rewards on referral likelihood. We focus on brand strength. Following Keller's (1993) work, we conceptualize strong brands as enjoying high brand awareness and well-established brand associations. Research shows that consumers respond to stronger and weaker brands differently. For example, a given price reduction will have a greater sales impact when it is applied to a higher-quality (stronger) brand than when it is applied to a lower-quality (weaker) brand (e.g., Blattberg and Wisniewski 1989; Heath et al. 2000). We also expect brand strength effects for rewarded referral. Consumers of stronger brands feel more brand commitment than consumers of weaker brands because their choices are affected more by preferences than by budget limits (Blattberg and Wisniewski 1989). This stronger commitment gives consumers of a stronger brand more confidence in making recommendations, thus increasing (unrewarded) referral likelihood and limiting the incremental impact of a reward. Furthermore, rewarding referral by consumers of a stronger brand may yield a perception that the reward compromises their commitment to and confidence in the brand (Bem 1965, 1972).

In contrast, consumers of a weaker brand are likely to have greater residual desire or lower choice confidence (Heath et al. 2000; Simonson 1992) and, thus, less WOM motivation. For these consumers, a reward may compensate for this lower residual desire and increase their choice confidence. Furthermore, the two groups may perceive the value of a reward differently. If consumers of weaker brands put more weight on price than consumers of stronger brands (Kamakura and Russell 1989), they would perceive a higher value from the (economic) reward and be more likely to be attracted by the reward program. Thus:

> H_2: The impact of offering a reward on referral likelihood depends on brand strength. The presence of a reward (compared with no reward) increases referral likelihood more for weaker brands than for stronger brands.

Method

Participants and design. Study 1 was a 3 × 2 × 2 between-subjects factorial experiment in which we varied the reward size (no reward, smaller, larger), the brand strength (weaker, stronger), and the tie strength (strong, weak). Two hundred seventy-five undergraduate students from a major university in Singapore were randomly assigned to the experimental conditions, except for brand strength, which we manipulated by having the respondents choose either a weaker or a stronger brand.

Procedure. We used portable MP3 players as the product category for the study because of the relevance of this product to the student participants. Students were first asked to imagine being in the market for an MP3 player and then were asked to pick the brand they preferred from the two alternatives (i.e., the stronger and weaker brand). To avoid the influence of prior brand beliefs, we did not use actual brand names, instead labeling the brands A and B. We manipulated brand strength in two ways. First, a brief description of reputation and quality was presented for each brand. The stronger brand was described as "one of the leading brands of electronic products, recognized for its high quality and reputation," and the weaker brand was described as a "relatively less-well-known player in the electronic products market, known for its reasonable quality and reputation." Second, expert ratings on several dimensions of the brand were provided, in which the quality rating and price of the stronger brand were higher (four of five stars, S$549, or approximately US$350) than those of the weaker brand (three stars, S$399). A picture and detailed product specifications were also included.

After making a choice, participants were asked to imagine that they had bought, used, and been very satisfied with the brand they had chosen. Product experience details were included to reinforce their satisfaction with the brand. The referral reward manipulation stated, "You are reminded that when you made the purchase, the salesperson told you that if you recommend the product to someone who then purchases the same model, the manufacturer would give you a shopping voucher of (S$50 [40], S$100 [80]), which can be redeemed at a leading local department store." We did not include this information in the no-reward condition.

Note that we used 10% and 20% of the product prices for the smaller and larger rewards, respectively. The use of a relative (rather than absolute) amount to determine reward size is consistent with the principle of relativity (Heath et al. 2000). We manipulated tie strength by asking participants to identify (using initials) either "one of your closest friends" for strong ties or a "casual acquaintance—someone you interact with from time to time, but someone not close enough to count as a friend (e.g., a classmate you have recently met)" for weak ties (Frenzen and Nakamoto 1993).

Next, participants indicated their referral likelihood on a scale anchored by 0% ("certain not to tell this person") and 100% ("certain to tell this person"). Manipulation check and covariate measures included tie strength (a four-item scale that Frenzen and Davis [1990] developed) and perceived reward size (the average of two nine-point items: "a very small amount/a very large amount" and "very unattractive/very attractive"). Then, participants were asked whether they could name the MP3 players used in the experiment. Finally, we included a nine-item, nine-point scale of product involvement (adapted from the work of Lichtenstein, Bloch, and Black [1988]) and the six-item market maven scale (Feick and Price 1987) to control for individual differences.

Results

Manipulation checks. Participants perceived the value of the larger reward as significantly greater than the smaller reward (mean smaller = 5.40, mean larger = 6.17; t(164) = 3.84, $p < .01$). Furthermore, mean tie strength ratings differed significantly (mean strong = .86, mean weak = .59; t(247) = 12.90, $p < .01$). Finally, 6.2% of the participants correctly identified at least one of the brands in the experiment and thus were dropped.

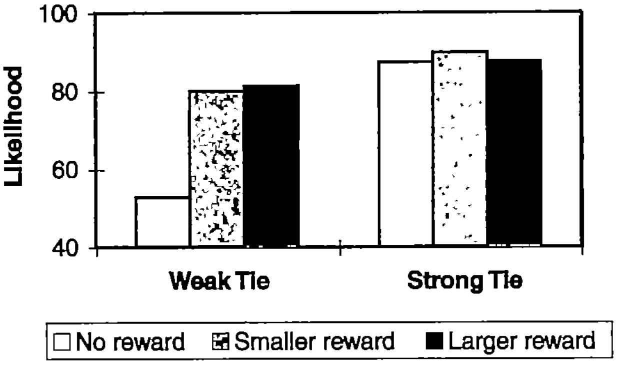
Referral likelihood. We analyzed referral likelihood with an analysis of covariance (ANCOVA). Participants' product involvement and market maven scores were covariates, and reward size, brand strength, and tie strength were between-subjects factors. The analysis yielded a significant main effect for market maven (F(1, 236) = 8.74, $p < .01$; β = .03). As market maven tendency increases, referral likelihood increases. This result is consistent with previous findings that indicate that market mavens exhibit a higher level of information provision than other consumers (Feick and Price 1987).

Two main effects for experimental variables were significant: tie strength (F(1, 236) = 63.49, $p < .01$) and reward (F(2, 236) = 22.67, $p < .01$). Referral likelihood was greater with strong ties (88.1%) than with weak ties (71.3%), a pattern consistent with previous studies (e.g., Frenzen and Nakamoto 1993). In addition, offering a reward significantly increased referral likelihood (no reward = 69.7%, smaller reward = 84.7%, larger reward = 84.1%). Contrasts of means revealed a significant difference between the no-reward and the smaller-reward conditions (t(168) = 4.89, $p < .01$) and between the no-reward and the larger-reward conditions (t(161) = 4.36, $p < .01$). The difference between the smaller- and larger-reward conditions was not significant (t(165) = .27, $p = .79$).

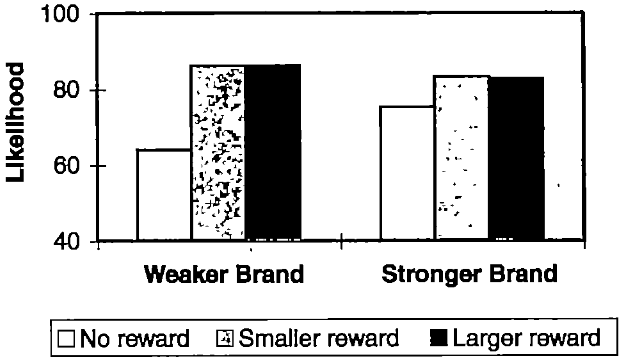
The main effect of reward was moderated by two significant two-way interactions (see Figure 1, Panels A and B). As H_1 proposed, there was a significant interaction between reward and tie strength (F(2, 236) = 22.65, $p < .01$). With strong ties, the presence of a reward did not affect referral likelihood (no reward = 87.2%, smaller reward = 89.7%, larger reward = 87.3%; F(2, 114) = .19, $p = .83$). In contrast, with weak ties, offering a reward increased consumers' referral likelihood (no reward = 52.6%, smaller reward = 79.8%, larger reward = 81.1%; F(2, 120) = 35.42, $p < .01$).

FIGURE 1
Study 1 Results

A: The Effect of Reward Size and Tie Strength on Referral Likelihood



B: The Effect of Reward Size and Brand Strength on Referral Likelihood



As H_2 proposed, there was a significant interaction between reward and brand strength (F(2, 236) = 5.28, $p < .01$). Offering a reward increased referral likelihood by more than 20 percentage points for the weaker brand but by less than 10 percentage points for the stronger brand (weaker brand: no reward = 63.7%, smaller reward = 86%, larger reward = 85.9%; F(2, 118) = 20.28, $p < .001$; stronger brand: no reward = 75.1%, smaller reward = 83.1%, larger reward = 82.6%; F(2, 126) = 2.52, $p < .10$). The effect is driven by the no-reward condition in which referral likelihood for the stronger brand is significantly higher than for the weaker brand (75.1% versus 63.7%; t(81) = 2.08, $p < .05$).

To gain insight into the mechanism underlying the effects of brand strength, we compared participants who chose the stronger (51.6%) and weaker (48.4%) brands. Participants evaluated both brands after their choice, and we computed the difference between the evaluation of the brands chosen and those not chosen. This difference was significantly larger for participants who chose the stronger brand than for those who chose the weaker brand (1.71 versus .53; t(248) = 6.64, $p < .01$). In addition, participants' relative ratings of the importance of price and quality in evaluating and choosing an MP3 player differed significantly (t(247) = 9.82, $p < .01$). Those who chose the stronger brand gave larger weights to quality than did those who chose the weaker brand (61.2/100 versus 46.5/100, respectively).

Discussion

Compared with offering no reward, offering a reward increased the likelihood of referral. Thus, the results suggest that referral reward programs can be effective. However, at least with the reward sizes we used, size does not matter. An increase in reward size did not increase referral likelihood. There are several possible explanations for this result. There may simply be a ceiling effect; that is, although the participants perceived the reward sizes as significantly different (based on the manipulation check), the smaller reward may have been large enough to generate the same effect as the larger reward. In addition, and more substantively, it may be that increases in reward size (which increase benefits of referral) also increase psychological and social costs by creating feelings of guilt about the inequity of the exchange (Austin and Walster 1974; Smith, Bolton, and Wagner 1999).

Weaker brands benefited more from offering a reward than did stronger brands. This result may be due to consumers of weaker brands having a lower level of commitment to or confidence in their brand and price being more important to them. Our results suggest the usefulness of referral reward programs for weaker brands.

Finally, consumers behaved differently when a reward was offered only with weak ties. With strong ties, there was no increase in referral likelihood with a reward. This point is critical in thinking about the marginal impact of referral reward programs. Programs need to be carefully crafted to achieve results greater than those that would have occurred in due course through naturally occurring WOM.

Study 2

Study 1 results are consistent with exchange theory, but we designed Study 2 to gain greater insight into the mechanism underlying the effects. With strong ties, we expect consumers to place greater weight on the sociopsychological costs and benefits of making a referral. If they are rewarded, they will produce thoughts related to these costs and benefits. With weak ties, we expect consumers to give less weight to (and produce fewer thoughts about) sociopsychological costs and benefits but to give more consideration to the economic benefits of the interaction.

Method

Study 2 was a 2 × 2 between-subjects design in which we manipulated the presence of a reward (no, small) and tie strength (strong, weak). Eighty-one Singaporean students were randomly assigned to the experimental conditions. Study 2 differed from Study 1 in that participants did not make a product choice but rather were asked to imagine that they had bought an MP3 player and were very satisfied with it. Furthermore, we provided a few detailed experiences with the product to simulate usage. In addition to Study 1 measures, in Study 2, we collected written thoughts about making a referral after collecting referral likelihood. We also measured perceptions of a referral's benefits and costs, using items developed from existing WOM research (Arndt 1967; Dichter 1966; Gatignon and Robertson 1986): For social benefits ($\alpha = .89$), we measured "others' perceptions of showing genuine concern," "helping others make the best choice," and "developing (maintaining) a good relationship with others," and for psychological costs ($r = .86$), we measured "feeling of being selfish" and "feeling of being motivated by money." Each item was evaluated on an 11-point (–5 to +5) scale, indicating how good or bad the consequence would be. More extreme ratings indicate higher weights.

Results

Perception ratings. Referral likelihood results replicate Study 1, and thus we do not describe them. To examine the mechanism, we ran 2 × 2 analyses of variance on the perceived social and psychological costs and benefits of referral. Tie strength (F(1, 77) = 20.4, $p < .01$) and reward (F(1, 77) = 4.60, $p < .05$) had significant main effects on social benefits. There are greater perceived social benefits with referral to a strong (3.14) than to a weak (1.59) tie and for no reward than for a reward (no reward = 2.74, reward = 1.95). The interaction between reward and tie strength was significant (F(1, 77) = 3.86, $p < .05$). With strong ties, there was little difference in the evaluation of social benefits, regardless of whether a reward was offered (no reward = 3.17, reward = 3.11; t(39) = .148, $p > .85$). With weak ties, less social benefit was perceived with a reward (.90) than without (2.30; t(40) = 2.61, $p < .01$).

Tie strength yielded a significant main effect on psychological costs (F(1, 77) = 11.70, $p < .01$). Perceived costs were greater for referral to a strong (–3.35) than to a weak (–1.73) tie. A reward also resulted in a significant main effect (F(1, 77) = 19.66, $p < .01$). Participants evaluated perceived costs less negatively when there was a reward than when there was no reward (no reward = –3.56, reward = –1.48). In addition, the interaction between reward and tie strength was significant (F(1, 77) = 4.35, $p < .05$). There was a greater difference between no reward and reward with weak ties than with strong ties (weak tie: no reward = –3.25, reward = –.29; strong tie: no reward = –3.86, reward = –2.79).

Thought listings. We developed three categories of thought types: social benefits, social costs, and psychological costs. Two independent judges who were blind to the study's purpose coded the data. Agreement between the judges was high (92.5%); disagreements were resolved by discussion. We ran separate 2 × 2 analyses of variance on the number of thoughts within each of the three categories. For social benefits, there was only a significant main effect of tie strength (F(1, 77) = 14.57, $p < .01$). There were more thoughts about social benefits of a referral for strong ties

(1.58) than for weak ties (.68). For social costs, the main effects of reward and tie strength were both significant (F(1, 77) = 5.60 and 7.37, $p < .05$ and $p < .01$, respectively). There were more thoughts about social costs with a reward (.55) than without (.24) and when the referral was to a strong (.58) than to a weak (.22) tie. Moreover, the interaction between reward and tie strength was significant (F(1, 77) = 4.36, $p < .05$). With weak ties, participants showed little difference in their thoughts about social costs, regardless of whether a reward was offered (no reward = .20, reward = .24; t(40) = .25, $p = .80$). With strong ties, however, there were more thoughts about social costs with a reward (.89) than without (.29; t(39) = 2.65, $p < .01$).

For psychological costs, there was a significant main effect of reward and tie strength (F(1, 77) = 52.04 and 4.31, $p < .01$ and $p < .05$, respectively). Participants generated more thoughts about the costs of making a referral when a reward was offered (.73) than when it was not (.00) and to strong (.45) than to weak (.29) ties. In addition, the interaction between reward and tie strength was significant (F(1, 77) = 4.31, $p < .05$). A reward yielded a greater increase in thoughts about psychological costs with strong ties than with weak ties (weak tie: no reward = .00, reward = .52; strong tie: no reward = .00, reward = .95).

Discussion

Study 2 provides direct support for our exchange theory argument. In general, the scales we used to measure costs and benefits and the thought listings were consistent and suggest that consumers evaluate the social and psychological costs and benefits of a referral differently when a reward is involved. The potential social benefits of a referral are perceived as lower and the social and psychological costs are perceived as higher when a reward is offered than when one is not. Tie strength also matters. Consumers perceive greater potential social and psychological costs and benefits when the referral is to strong ties in the presence of rewards. In contrast, consumers tend to discount the importance of social and psychological costs and benefits and are more likely to recognize economic benefits when the referral is to weak ties.

Study 3

Studies 1 and 2 suggest that rewards matter and that their impact depends on tie strength and brand strength. What cannot be determined from these studies is whether it matters to whom the reward is given.

Referral Reward Schemes

Sales promotion benefits typically are provided only to the customer who makes use of the promotion. However, in customer referral programs, because there is an existing customer who makes a recommendation and a new customer who receives the referral, there could be three reward schemes. The first is "Reward Me," in which the recommender (the existing customer) receives the reward. This scheme is the focus in Studies 1 and 2 and, seemingly, the most typical in practice. In addition, however, there could be a scheme called "Reward You," in which the receiver of the recommendation (the new customer) receives the reward. Finally, there could be a blend of the two scenarios, or "Reward Both."

Costs and benefits vary depending on the scheme. The personal economic benefit that accrues to the existing customer is affected. He or she receives the full benefit for Reward Me, partial benefit for Reward Both, and nothing for Reward You, but the potential social and psychological costs decrease in the same order. The offsetting of economic gains by psychological/social costs makes it difficult to predict a main effect of reward scheme.

We propose tie strength as a moderator. We expect that consumers will weight benefits and costs differently and will be governed by different rules of exchange depending on the receiver of the recommendation. In recommending to weak ties, consumers are motivated more by self-interest and are less concerned about psychosocial dimensions. Thus, with weak ties, we expect the lowest referral likelihood for Reward You. Our weak ties prediction is also based on an equity argument; specifically, people expect to receive resources (e.g., rewards) in exchange for resources (e.g., referral) they provide (Walster, Berscheid, and Walster 1973; Walster, Walster, and Berscheid 1978). With Reward You, inequity exists because the consumer receives nothing in return for a referral. Conversely, with Reward Me, the recommender is rewarded, and balance is achieved, increasing referral likelihood. Reward Both should be in between.

With strong ties, consumers attempt to maximize mutual benefits for the relationship as a whole, regardless of which member receives the greater individual reward (Kelly 1979; Kelly and Thibaut 1978). Furthermore, consumers are likely to help strong ties without expecting any economic return and enjoy psychological and/or social benefits by helping a strong tie obtain a reward. This logic implies an ordering for referral likelihood that is the opposite of that for weak ties. Thus:

> H_3: The impact of reward allocation scheme on referral likelihood depends on tie strength. With weak ties, consumers are most likely to make a referral in the Reward Me condition, followed by Reward Both and Reward You. With strong ties, consumers are most likely to make a referral in the Reward You condition, followed by Reward Both and Reward Me.

Method

One hundred thirty-six undergraduate students from a Singaporean university participated in a 3 × 2 between-subjects factorial experiment in which we varied the scheme of the reward distribution (Reward Me, Reward You, Reward Both) and tie strength (strong, weak). The experimental procedure of Study 3 was identical to Study 2 except for the reward scheme. We manipulated scheme by varying who received the referral reward (a shopping voucher): the recommender, the receiver of the recommendation, or both.

Results

Manipulation checks. Manipulations of reward scheme and tie strength were successful. Participants perceived reward value similarly across reward schemes (Reward Me = 6.29, Reward You = 5.95, Reward Both = 5.83;

F(2, 133) = 1.84, $p = .16$), and tie strength was significantly greater with strong ties (.85) than with weak ties (.55; t(135) = 12.21, $p < .01$).

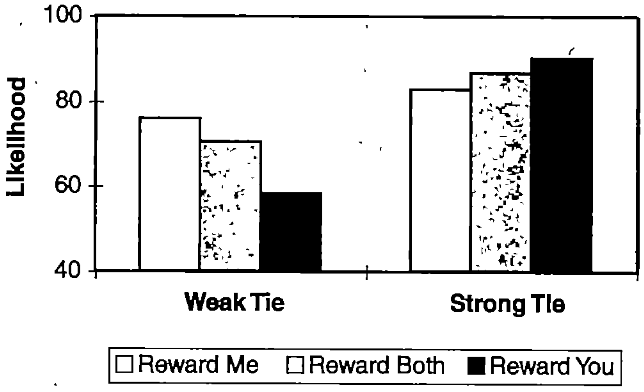
Referral likelihood. We ran an ANCOVA on referral likelihood with reward scheme and tie strength as between-subjects factors and product involvement and market maven as covariates. As in Study 1, the market maven covariate was significant (F(1, 128) = 8.86, $p < .01$), and there was a significant main effect of tie strength (strong ties = 86.5%, weak ties = 68.7%; F(1, 128) = 42.53, $p < .01$).

As H_3 predicted, there was a significant interaction between reward scheme and tie strength (F(2, 128) = 4.54, $p < .01$; see Figure 2). With strong ties, differences among reward schemes were not significant, though they were directionally consistent with our prediction (F(2, 62) = .98, $p = .38$; Reward You = 90.1%, Reward Both = 86.7%, and Reward Me = 82.8%). Conversely, with weak ties, differences were significant (F(2, 64) = 4.37, $p < .05$) and in the predicted order (Reward You = 58.3%, Reward Both = 70.4%, and Reward Me 75.8%). Reward You is marginally lower than Reward Both (t(42) = 1.90, $p = .06$) and is lower than Reward Me (t(44) = 3.15, $p < .01$), but the latter two are not significantly different from each other (t(46) = 1.21, $p = .23$).

Discussion

Study 3 illustrates the importance of considering the target of the reward when designing referral reward programs. The reward's distribution between the existing and the new customer had different effects on consumers' likelihood of making a referral, depending on the relationship between the recommender and the receiver of the recommendation. Study 3 showed that varying the recipient of the reward has little effect on referral likelihood when the recipient is a strong tie, though the direction favors rewarding the new customer (or both). With weak ties, a reward for the recommender (existing customer) seemed to work best. The results are consistent with the framework we proposed; that is, psychological and social benefits and costs are more important with strong ties, and economic benefits and costs are more important with weak ties.

FIGURE 2
Study 3: The Effect of Reward Scheme and Tie Strength on Referral Likelihood



Study 4

In Studies 1–3, we used student participants who reacted to a scenario about MP3 players. We designed Study 4 to examine the generalizability of these findings using adult consumers' actual experiences with mobile phone service.

Method

Design. Study 4 was a 3 × 2 × 2 between-subjects factorial experiment in which we varied reward scheme (No Reward, Reward Me, Reward Both), brand strength (weaker, stronger), and tie strength (weak, strong). Participants were randomly assigned to the experimental conditions, except in the case of brand strength, which we measured.

Participants. Two hundred ninety-eight adult consumers were recruited from executive programs at a South Korean university. The participants, 61% of whom were men, were employed and had a median age of 36 at the time of the study.

Stimuli and manipulations. We chose mobile phone service because it differs in important ways from MP3 players. It is a service (not a good), it has several intangible features, and some of the critical attributes are based on experience (not search) characteristics. In addition, high consumer involvement and long market availability are likely to make WOM important, influential, and prevalent for mobile phones. Finally, mobile service is familiar and relevant to our respondents and is not gender specific.

In Study 4, participants responded on the basis of their own experience with their current mobile phone service. In Korea, there are three major mobile service providers, and at the time of the study, the leading brand had a 53% market share, the longest presence in the market, and a reputation for high quality and high price. The two follower brands had 31.5% and 15.5% market shares, respectively, with a reasonable or low quality and price image. Customers of the leading brand were assigned to the stronger brand condition, and customers of the two follower brands were assigned to the weaker brand condition. We use manipulation checks to confirm our expectations about brand perceptions.

To manipulate reward scheme, we included No Reward, Reward Me, and Reward Both conditions. We excluded the Reward You condition to simplify the study because it is much less common in practice. The reward was 60,000 Korean won in free calls (about $50 at the time of the study) in the Reward Me condition or 30,000 won in free calls each in the Reward Both condition. We manipulated tie strength as previously.

Procedure. After answering basic questions about their mobile phone service, participants responded to the tie strength manipulation. Next, they were told that their current mobile phone service provider was beginning a referral reward program. This part was not presented in the No Reward condition. Then, they read a mobile phone–related WOM scenario in which they were asked to imagine discovering that the individual described previously was considering a new or changed mobile phone service.

Measures. Because participants had real brand experience, we needed a referral likelihood measure that included valence and extremity. We used two nine-point items ("strongly recommend that they not subscribe to the service/strongly recommend that they subscribe to the service" and "sure to tell the friend [acquaintance] not to join the service/sure to tell the friend [acquaintance] to join the service") to measure referral likelihood (Blodgett, Hill, and Tax 1997).

We used the same manipulation checks for tie strength and perceived value of rewards as in Studies 1 and 3. We also measured (on seven-point scales) perceived reputation, quality, and price of the participants' brands. Again, we included product involvement and market maven scales as covariates. In addition, we included three seven-point items that measured brand satisfaction ("dissatisfied/satisfied," "displeased/pleased," and "unfavorable/favorable"; Crosby and Stephens 1987).

Results

Manipulation checks. Of the participants, 56% were customers of the leading brand, and 44% were customers of one or the other of the followers. Perceived brand reputation, quality, and price of the stronger brand were significantly higher than those of the weaker brands (reputation: 5.18 versus 4.79; $t(292) = 2.25$, $p < .05$; quality: 5.09 versus 4.35; $t(292) = 5.47$, $p < .01$; price: 3.92 versus 3.43; $t(292) = 3.40$, $p < .01$). Mean tie strength ratings also differed significantly (.88 for strong ties and .66 for weak ties; $t(292) = 11.45$, $p < .01$). Participants perceived the reward as being of the same value in the two reward conditions (Reward Me = 5.01, Reward Both = 5.18; $t(197) = .62$, $p > .50$).

Referral likelihood. The two items measuring referral likelihood were highly correlated ($r = .93$), and we averaged them. We analyzed referral likelihood with an ANCOVA. Participants' product involvement, market maven, and satisfaction scores were covariates, and reward scheme, brand strength, and tie strength were between-subject factors. The analysis yielded a significant main effect for all three covariates ($F(1, 275) = 10.01$ to 14.85, all $ps < .01$). Increases in market maven ($\beta = .27$), involvement ($\beta = .27$), and satisfaction ($\beta = .18$) yielded increases in referral likelihood.

Main effects for tie strength ($F(1, 275) = 16.77$, $p < .01$) and reward scheme ($F(2, 275) = 10.66$, $p < .01$) were significant. Again, there was greater referral likelihood with strong ties (6.37) than with weak ties (5.67). In addition, referral likelihood was greatest when both customers were rewarded and lowest when neither was (Reward Both = 6.51, Reward Me = 6.12, and No Reward = 5.43). The differences between No Reward and Reward Me ($t(195) = 3.08$, $p < .01$) and between No Reward and Reward Both ($t(195) = 4.37$, $p < .01$) were significant, but the difference between Reward Me and Reward Both was not.

There was a significant interaction between reward scheme and tie strength ($F(2, 275) = 5.19$, $p < .01$; see Figure 3). In the strong tie condition, referral likelihood for Reward Both (6.79) was marginally greater than Reward Me (6.17; $t(103) = 1.89$, $p = .06$) and greater than No Reward (6.13; $t(101) = 2.49$, $p < .05$). Reward Me and No Reward were not different from each other ($t(100) = .82$, $p = .42$). Conversely, with weak ties, referral likelihood was greater for both Reward Me (6.08) and Reward Both (6.19) than for No Reward (4.72; $t(93) = 3.66$, $p < .01$; $t(92) = 3.80$, $p < .01$; respectively). The difference between Reward Me and Reward Both was not significant.

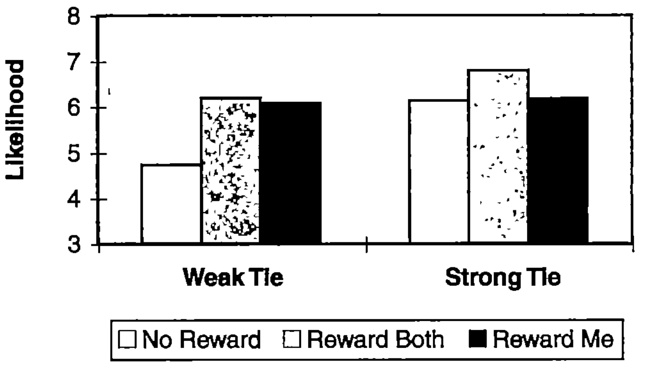
In addition, the interaction between reward scheme and brand strength was significant ($F(2, 275) = 3.35$, $p < .05$). For the stronger brand, referral likelihood was greater for Reward Both (6.90) than for No Reward (5.80; $t(107) = 3.90$, $p < .01$). Reward Me (5.90) was not different from No Reward ($t(109) = .83$, $p = .41$), but it was different from Reward Both ($t(114) = 3.32$, $p < .01$). For the weaker brands, referral likelihood was greater for both Reward Me (6.41) and Reward Both (6.02) than for No Reward (5.01; $t(84) = 3.55$, $p < .01$; $t(86) = 2.37$, $p < .05$; respectively). The difference between Reward Me and Reward Both was not significant ($t(84) = 1.08$, $p = .28$).

Discussion

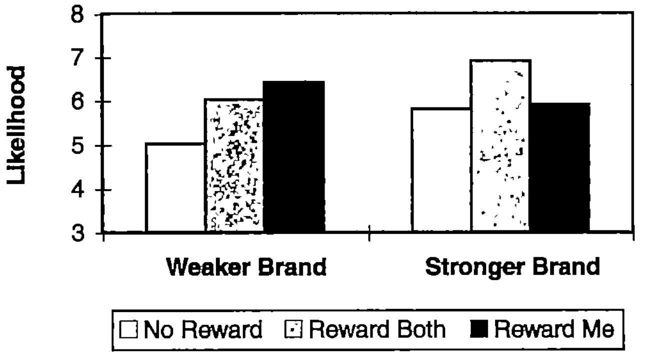
Study 4 replicated the moderating effects of both tie strength and brand strength on referral likelihood that we

FIGURE 3
Study 4 Results

A: The Effect of Reward Scheme and Tie Strength on Referral Likelihood



B: The Effect of Reward Scheme and Brand Strength on Referral Likelihood



found in Studies 1 and 2. A reward offered to an existing customer who makes a referral (i.e., Reward Me) increased referral likelihood to weak ties but not to strong ties (H_1). We also found that referral likelihood was greater when the reward was offered by a weaker brand (H_2). Furthermore, Study 4 results were similar to those of Study 3 for the interaction of tie strength with reward scheme. There was little difference between Reward Both and Reward Me with weak ties. With strong ties, referral likelihood was greater with Reward Both than with Reward Me (H_3).

In Study 4, we also found an interaction between brand strength and scheme. For the stronger brand, Reward Both performed significantly better than Reward Me, whereas for the weaker brand, Reward Me fared slightly (albeit not significantly) better than Reward Both. This result has direct implications for the design of reward programs. Furthermore, this interaction is similar to the one between tie strength and scheme, perhaps for similar reasons. It is possible that for consumers of a stronger brand, Reward Me induces negative self-perceptions because of their high level of commitment to the brand and strong intrinsic motivation for referral. Conversely, Reward Both may reduce such psychological costs. In addition, the incremental economic gain of Reward Me over Reward Both is likely to be perceived as less important by consumers of a stronger brand, because they tend to be less price sensitive.

General Discussion

Contributions to Theory

This article makes several contributions to the literature on WOM and exchange theory. First and at the most basic level, our work broadens the scope of exchange theory from a focus on exchange between two parties (for a discussion of types of exchange, see Ekeh 1974) to the examination of a more complex relationship among an existing customer, a new customer, and a brand. Furthermore, although exchange theory has been used to examine a wide range of behaviors, scholars have rarely approached WOM from this perspective (an exception is Gatignon and Robertson's [1986] conceptual study). We believe that our findings show the utility of applying exchange theory to understanding WOM. In the equity view of exchange, people prefer an equitable or balanced exchange, and in the presence of an inequitable or unbalanced exchange, they feel distress and try to remedy the situation by either reducing their input or increasing their output to achieve equilibrium (Walster, Berscheid, and Walster 1973; Walster, Walster, and Berscheid 1978). Our finding that rewards increase people's referral likelihood supports the exchange theory explanation. That is, making a referral without any extrinsic reward may create feelings of inequity for a customer; the referral is an unreciprocated favor done for the other consumer and the company. In this framework, rewards for referral work because they reduce the level of inequity and create movement toward equilibrium. The lack of difference in referral likelihood between smaller and larger rewards can be interpreted in the same light; that is, the larger reward may have been perceived as too much compensation for a referral (Austin and Walster 1974; Smith, Bolton, and Wagner 1999).

We expected that equity concerns would dominate in casual relationships but not in close relationships. In close relationships, people respond to the other person's needs, and we linked our prediction for these relationships to the concept of strong ties (Clark 1984; Clark, Mills, and Powell 1986; Granovetter 1973). The prediction for close relationships was supported; the presence or amount of reward did not affect referral likelihood.

Our research also increases the understanding of the operation of norms or rules of exchange by examining how reward allocation influences referral likelihood. Because the recommender receives the full economic benefit with Reward Me, partial benefit for Reward Both, and nothing for Reward You, the level of equity in exchange is in the same order (i.e., the greatest inequity is with Reward You). For weak ties, referral likelihood is directly linked to the amount of equity. For strong ties, in which equity should not matter, we found that the link between equity and referral likelihood was broken.

Implications for Managers

In general, our results show that offering a reward increases referral likelihood but that there was no difference in effect between smaller and larger rewards. These results suggest that firms need to calibrate reward size carefully by computing the revenue impact of the size of a reward on marginal referral likelihood and then comparing that with the cost of alternative reward programs.

Studies 1 and 2 found that with strong ties, rewarding the existing customer (Reward Me) did not increase referral likelihood. For marketing managers, the results create a challenge. Referral reward programs tend to target strong ties explicitly (e.g., cell phone family-and-friends programs) or end up with strong ties (because people interact most frequently with strong ties, these ties are more likely to receive recommendations). A solution may be the allocation scheme. The results of Studies 3 and 4 suggest that rewarding either the new customer or both the new and the existing customer can increase referral likelihood with strong ties (though not by much). In addition, our study examined only referral likelihood. Rewards may have other effects on strong ties; perhaps they serve as a reminder to talk about the brand, even to friends.

Conversely, rewards are important for increasing referral likelihood to weak ties. Frenzen and Nakamoto (1993) find that weak ties are not as effective as strong ties in the flow of certain types of information, though they play a critical role in bridging the gap between different groups (Granovetter 1973). Although our results show that information transmission through weak ties can be improved with incentives, the managerial issue is how to devise programs that target weak ties. The first referrals from a customer will probably be family or close friends for whom the recommendation is likely to have occurred anyway. It is probably subsequent referrals, presumably to weaker ties, that need encouragement. An option would be to increase the reward as the number of referrals increases. This segmentation approach would pay the least for referrals that are most likely to occur naturally (i.e., strong ties) and the most for referrals that are least likely to occur naturally (i.e., weak ties).

Furthermore, the results in Studies 3 and 4 show that with weak ties, the recommender needs to receive something in return for the recommendation. The reward scheme could be calibrated to reflect this result by tilting the payoff toward the recommender for the subsequent referrals. Our results in Study 4 support this notion; the referral levels with strong ties drop off as the reward switches from Reward Both to Reward Me. Thus, tilting the rewards toward the recommender should naturally switch the emphasis to weak ties.

In Study 1, we also found that the impact of reward programs on referral likelihood varied by brand strength. The increase in referral likelihood with a reward compared with no reward was much greater for the consumers of the weaker brand than for the consumers of the stronger brand. These results imply that referral reward programs may be particularly important for brands that are perceived as weaker. Even if the focus is on increasing brand strength in the long run, in the short run, weaker brands can use a reward program to increase referrals and, perhaps, product trial. As we noted in Study 4, our results provide managers with guidance in the choice of scheme by brand strength; specifically, they should use Reward Me for weaker brands and Reward Both for stronger brands.

Limitations and Further Research

We concentrated on the recommender's referral likelihood, but for a referral program to be effective, there must be referrals combined with receiver receptivity. Receivers may form different perceptions of the recommender and evaluate the brand differently if a referral arises from a reward program rather than from naturally occurring WOM (for a related idea, see Wiener and Mowen 1986). Thus, further research should more explicitly focus on the dyad, examining reward program conditions under which both referral likelihood and receiver receptivity are high. In addition, because it is possible that referral likelihood does not always lead to actual referrals (Mittal and Kamakura 2001), further research should collect behavioral data to complement and validate our findings.

Kivetz and Simonson (2002) show that as consumers invest more effort to obtain a reward in a frequency program, their preference moves more toward luxury rewards. This result may have implications for ours. If referral requires relatively high levels of recommender effort, our use of more utilitarian/functional rewards might have underestimated the potential effects of referral programs. It seems worthwhile to consider different types of rewards in further research.

In general, communicating an opinion makes the communicator's attitude more extreme, even when the opinion is not the communicator's own (Higgins and Rholes 1978). In addition, self-perception theory argues that a behavior induced by or associated with a large extrinsic incentive is likely to lead to overjustification and thus affect the person's attitudes negatively (Bem 1972; Festinger 1957). The results of this work indicate that though engaging in natural WOM may reinforce recommenders' satisfaction with the brand, making rewarded referrals may undermine it. In examining rewarded referral, further research should examine other downstream variables (e.g., brand attitude, satisfaction, brand loyalty) in the recommender.

Our research designs assumed that consumers learn about the referral reward program after product purchase. However, consumers can also learn about such programs before purchase. If so, the program could affect brand choice positively if it is perceived as an added value of the brand. Offering a reward might also activate persuasion knowledge for some consumers, leading them to make negative inferences about the firm's motives and perhaps leading them to less favorable responses toward the brand (Freistad and Wright 1994). Further research should examine the impact of pre- versus postpurchase knowledge of the reward program.

Finally, the role of cultural differences should be considered. All our participants were from Asia. Asians are more likely to have an interdependent self-construal, whereas Westerners are more likely to be independent (Aaker and Lee 2001). Because self-construal affects a person's assessment of the importance of the self versus the group, the (presumed) interdependent self of our participants may have exerted systematic effects on their referral likelihood in interacting with strong versus weak ties. There are two possible effects. On average, if Asians show more strong-tie-oriented (e.g., altruistic) behaviors regardless of tie strength, they should make little distinction in their referral behavior between strong and weak ties. As a result, the significant interactions between tie strength and other variables that we found would seem to be unlikely. Conversely, if Asians show more altruistic behavior with strong ties and more selfish behavior with weak ties than Westerners, this extremity will inflate the moderating effects of tie strength for Asians. Only a cross-cultural comparison or a design incorporating a manipulation of self-construal can examine the impact of self-construal. Because our tie strength findings are consistent with previous studies that use U.S. participants (e.g., Frenzen and Nakamoto 1993), we anticipate that our effects would persist with a Western sample.

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Luigi M. De Luca & Kwaku Atuahene-Gima

Market Knowledge Dimensions and Cross-Functional Collaboration: Examining the Different Routes to Product Innovation Performance

There is consensus in the marketing literature that market knowledge and cross-functional collaboration are two fundamental resources for successful product innovation. However, few studies examine the dimensions or characteristics of market knowledge and how and why these resources influence product innovation performance. Drawing on contingency theory and the knowledge-based view of the firm, the authors argue that knowledge integration mechanisms may account for the effects of market knowledge dimensions (i.e., breadth, depth, tacitness, and specificity) and cross-functional collaboration on product innovation performance. They find that market knowledge specificity and cross-functional collaboration affect product innovation performance through knowledge integration mechanisms. In contrast, whereas the effect of market knowledge depth is partially mediated, market knowledge breadth has a direct, unmediated effect on product innovation performance. A test of an alternative moderating perspective shows that the effects of market knowledge depth and cross-functional collaboration on product innovation are negatively moderated by knowledge integration mechanisms. By showing the differential effects of market knowledge dimensions on product innovation performance, the authors provide a more refined understanding of the interplay among market knowledge, its integration, and the firm's performance in product innovation. The authors also conclude that by overlooking the role of knowledge integration mechanisms, previous research may have provided an overly optimistic view of the value of cross-functional collaboration in product innovation.

The marketing literature has established that product innovation performance is enhanced by three distinct yet highly complementary factors: market knowledge (Atuahene-Gima 1995, 2005; Day 1994; Li and Calantone 1998), cross-functional collaboration (e.g., Griffin and Hauser 1996; Kahn and Mentzer 1998, Song and Parry 1997), and knowledge integration mechanisms (hereinafter KIMs; see also Madhavan and Grover 1998; Maltz and Kohli 2000; Ruekert and Walker 1987). Market knowledge refers to the firm's knowledge about its customers and competitors (Day 1994; Kohli and Jaworski 1990; Narver and Slater 1990). Cross-functional collaboration refers to the degree of cooperation and the extent of representation by marketing, research and development (R&D), and other functional units in the product innovation process (Kahn 1996; Li and Calantone 1998; Song, Montoya-Weiss, and Schmidt 1997). Knowledge integration mechanisms refer to the formal processes and structures that ensure the capture, analysis, interpretation, and integration of market and other types of knowledge among different functional units within the firm (Olson, Walker, and Ruekert 1995; Zahra, Ireland, and Hitt 2000). The inability of firms to manage the interplay of these factors lies at the root of many failures in product innovation. For example, Fisher, Maltz, and Jaworski (1997, p. 54) report several examples, such as Texas Instruments's unsuccessful early entry into the desktop personal computer business, and Hewlett-Packard's early entry into the laptop business with a technology-oriented 23-pound laptop.

Although the contributions of previous studies are substantial, extant research is lacking in three respects. First, the knowledge-based view (hereinafter KBV) of the firm underscores the importance of several different dimensions of market knowledge in product innovation: breadth, depth, specificity, and tacitness (see Galunic and Rodan 1998). However, although studies in marketing emphasize the importance of broad market knowledge as reflected in the concept of market orientation (e.g., Atuahene-Gima 2005; Atuahene-Gima, Slater, and Olson 2005; Jaworski and Kohli 1993; Li and Calantone 1998), there is little or no insight into the relative importance of the different dimensions of market knowledge as drivers of product innovation performance. Given the strategic importance of market knowledge, an approach that considers its dimensions and parses out their distinct contributions seems appropriate if

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we are to examine how market knowledge matters in product innovation performance.

Second, previous studies have focused almost entirely and separately on the effects of market knowledge (e.g., Atuahene-Gima 1995, 2005; Li and Calantone 1998) and cross-functional collaboration (e.g., Kahn 1996; Song, Montoya-Weiss, and Schmidt 1997) on product innovation outcomes. No detailed explanations are offered as to how and why KIMs matter in these relationships. Yet it is often implicitly assumed that KIMs are salient factors in transforming market knowledge and cross-functional activities into product innovation performance (Griffin and Hauser 1996; Hoopes and Postrel 1999). The current state of the literature is lacking and inconsistent because a key assumption of the KBV is that it is not knowledge itself but rather its integration among functional units in the firm that drives sustainable competitive advantage (Grant 1996a). For this reason, product innovation is often characterized as a process by which a firm transforms knowledge embedded in cross-functional teams into new products (Madhavan and Grover 1998, p. 2). Understanding how market knowledge and cross-functional collaboration are transformed into innovation outcomes through KIMs may shed light on the salience of this factor, which the KBV suggests is at the root of the firm's competitive advantage.

Third, KIMs have traditionally been positioned as moderators in the relationship between sources of information and the breadth and depth of the firm's knowledge (Zahra, Ireland, and Hitt 2000) and between internal and external capabilities and innovation outcomes (Zahra and Nielsen 2002). Still, there is another view based on structural contingency theory that suggests that because knowledge characteristics (e.g., complexity) make communication flow difficult among functional units, knowledge becomes a key contingency factor that determines the nature of integration designs (Thompson 1967). Furthermore, the increased information-processing requirements resulting from interdependence among functional units can be met only by corresponding increases in information-processing capacity through the design of coordination mechanisms (e.g., Galbraith 1973; Thompson 1967). This view implies that market knowledge and cross-functional collaboration affect performance through their effects on the design of KIMs.

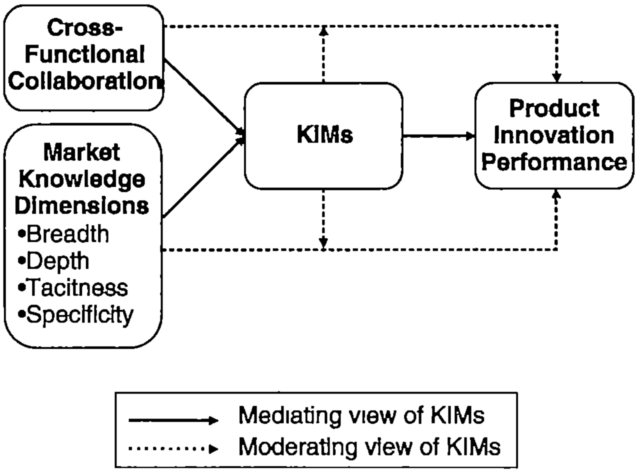
Extant research in marketing has paid little attention to these different perspectives of the role of KIMs. The moderating view suggests that both market knowledge and cross-functional collaboration are inherently valuable such that KIMs determine the strength of their effect on innovation performance. In contrast, the mediating view suggests that these resources are not inherently valuable and that they could affect innovation performance through their effects on KIMs. Because marketing theory has placed considerable weight on the value of market knowledge and cross-functional collaboration for effective product innovation and because of the widely held belief among managers that value creation involves knowledge integration among functions, examining these perspectives is particularly important in advancing this research stream. If the "active role" of KIMs is as a mediator rather than as a moderator or if it plays both mediator and moderator roles, marketing managers may need to reevaluate their stance toward the role of market knowledge and cross-functional collaboration per se in product innovation. The findings also shed light on what level of importance researchers and managers need to place on the inherent value of both resources. Figure 1 presents our conceptual model.

Theory Development

Contingency theory has been one of the major strands of thinking about firms and their structures and strategic actions (Galbraith 1973). Drazin and Van de Ven (1985) note two fundamental strands of contingency theory. The first is the "fit-as-mediation" view (Venkatraman 1989), which posits that managers choose or adopt organizational structures, processes, and strategies that reflect the particular circumstances of their organizations (Galbraith 1973, p. 2). In particular, because the organization is essentially an "information-processing network" the objective of organizational design is to achieve an efficient correspondence between the information-processing requirements of its strategic contingencies and the information-processing capabilities of its integration mechanisms (Galbraith 1973, p. 6). Thus, this theory asserts that by increasing the information-processing demands in the firm, strategic interdependence or collaboration among functions dictate the type and degree of organizational integration mechanisms adopted to transfer knowledge within the firm (see Kumar and Seth 1998; Thompson 1967).

The KBV suggests that knowledge is sticky; in other words, its characteristics make it difficult, costly, and uncertain to transfer and recombine within the firm (e.g., Galunic and Rodan 1998; Grant 1996a; Szulanski 1996). For this reason, Birkinshaw, Nobel, and Ridderstråle (2002) and others (e.g., Germain and Droge 1997) argue that the characteristics of knowledge complicate the process of transfer by increasing uncertainty and ambiguity and, through this

FIGURE 1
Conceptual Model of the Role of Cross-Functional Collaboration, Market Knowledge Dimensions, and KIMs in Product Innovation


Cross-Functional Collaboration
Market Knowledge Dimensions
•Breadth
•Depth
•Tacitness
•Specificity
KIMs
Product Innovation Performance
Mediating view of KIMs
Moderating view of KIMs

complication, increase the likelihood that firms will develop appropriate KIMs. In this view, knowledge characteristics are the fundamental quality to which managers adapt organizational integration structures. Consistent with the KBV, market orientation theory indicates that market knowledge generation is an outside-in process and that firms use internal processes to integrate the acquired knowledge (Day 1994; Jaworski and Kohli 1993). If the KBV tenet is accepted—that is, it is not knowledge per se but rather its integration that affects competitive advantage (Grant 1991, 1996b)—it suggests that KIMs are mediators of the link among market knowledge dimensions, cross-functional collaboration, and firm performance.

The second strand of contingency theory is the interactive fit argument, or "fit-as-moderation" view (Venkatraman 1989). This view proposes that the firm's performance is attributable to a match between its strategic behaviors and the internal and external environment conditions (Atuahene-Gima and Murray 2004; Zeithaml, Varadarjan, and Zeithaml 1988). This suggests that KIMs moderate the effect of market knowledge and cross-functional collaboration on performance. Given the limited attention the mediating view of KIMs has received, we focus on this perspective, though we also empirically examine the moderating view.

Effect of Market Knowledge Dimensions on KIMs

KIMs. According to Barki and Pinsonneault (2005, p. 166), integration captures the extent to which distinct but interdependent functional units, departments, and resources are coordinated or made to constitute a unified whole. The task of integration or coordinating interfunctional interactions is often accomplished by the use of structures and processes (see Griffin and Hauser 1996; Sobek, Liker, and Ward 1998). As Olson, Walker, and Ruekert (1995, p. 49, emphasis in original) note, integration mechanisms are "*lateral linkage devices or structural coordination mechanisms*" that firms use to coordinate cross-functional interactions (see also Griffin and Hauser 1996, p. 203). Following Zahra, Ireland, and Hitt (2000, p. 930), we define KIMs as structures and processes, such as the use of documentation, information-sharing meetings, analysis of successful and failed projects, project reviews, and briefings by external experts and consultants, that ensure the capture, analysis, interpretation, and combination of knowledge within the firm. These structures and processes enable managers to determine systematically and understand what has been learned in the product innovation process, to interpret and articulate the importance of the learning, and to devise ways to exploit the knowledge competitively (Zahra and Nielsen 2002).

Market knowledge dimensions. Information about the market environment, particularly about customers and competitors, is the source of stimulation for the firm's knowledge (Day 1994; Nonaka 1994, p. 27) and the driver of a market-oriented strategy (Day and Nedungadi 1994, p. 32). This implies that a firm that correctly identifies, collects, and uses information about customer and competitor conditions is deemed to be knowledgeable about the market. Knowledge about technology and other environmental properties is important, but only to the extent that it enhances the understanding of customers' and competitors' behavior. For this reason, Srinivasan, Lilien, and Rangaswamy (2002, p. 49) show that the firm's ability to sense and respond to technology developments per se is different from its market orientation, that is, the ability to sense and respond to customers and competitors. Thus, we define market knowledge as the firm's knowledge of its customers' behaviors and needs as well as its competitors' behavior. We examine the effects of four characteristics of market knowledge on KIMs: breadth, depth, tacitness, and specificity.[1]

Knowledge breadth refers to the number of different knowledge domains with which the firm is familiar (Bierly and Chakrabarti 1996). Prabhu, Chandy, and Ellis (2005, p. 116) offer a similar view, referring to knowledge breadth as the range of fields over which the firm has knowledge. We define "market knowledge breadth" as the firm's understanding of a wide range of diverse customer and competitor types and factors that describe them. In other words, a firm is said to have broad market knowledge if it has knowledge of a wide variety of current and potential customer segments and competitors and also uses a diverse set of parameters related to customers (e.g., needs, behaviors, characteristics) and competitors (e.g., products, markets, strategies) to describe and evaluate them (e.g., Zahra, Ireland, and Hitt 2000). This concept highlights the broad understanding of customers and competitors that is deeply rooted in the market orientation construct.

Firms with a broad knowledge base have a greater potential to recombine different elements of the knowledge to improve opportunity recognition and creative potential (Kogut and Zander 1992). However, knowledge breadth might hamper knowledge recombination because the high degree of heterogeneity of knowledge elements contributes to the complexity of transfer across functional units (Galunic and Rodan 1998). In contrast, limited market knowledge can be easily disseminated to and internalized by members of different departments. Furthermore, because customer segments and competitors' strategies change over time, broad market knowledge may involve frequent and numerous variations that further increase the difficulties of cross-functional transfer. In addition, when market knowledge is broad, not all of it can be usefully employed in every innovation project. Bringing in marginally useful information or leaving out relevant information might be detrimental to performance (Leonard-Barton 1992). Thus, the increased difficulties in sharing broad knowledge lead managers to develop KIMs to provide the necessary information-processing capacity for the organization. Empirically, Germain and Droge (1997) find that the breadth of the firm's knowledge about a task is an antecedent to processes for knowledge integration because these processes are the necessary mechanisms to combat excessive compartmentalization of the diverse knowledge. Thus:

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[1] Galunic and Rodan (1998) identify another characteristic of knowledge, namely, knowledge dispersion. We contend that this characteristic is reflected in the construct of market knowledge breadth because it captures different elements underlying market knowledge (Turner and Makhija 2006).

> H_1: The broader the market knowledge, the greater is the use of knowledge integration mechanisms.

Prabhu, Chandy, and Ellis (2005) describe technical knowledge depth as the amount of within-field knowledge the firm possesses. McEvily and Chakravarthy (2002) also argue that complex knowledge reflects the degree to which knowledge consists of many different, unique, and interdependent elements, such that knowing how one element works reveals little about how the different elements work together. Consequently, we define "market knowledge depth" as the level of sophistication and complexity of a firm's knowledge of its customers and competitors. It captures the level of sophistication with which the firm is able to connect the unique and interdependent relationships among the factors that describe key issues about customers and competitors. Knowledge of the interdependencies of elements such as customers' needs, behaviors, and preferences and competitors' products and strategies indicates that a firm has a deep understanding of its market. Thus, whereas breadth captures the horizontal dimension of knowledge, depth captures the vertical dimension.

There are two reasons market knowledge depth should affect KIMs. First, deep market knowledge implies high and complex interdependencies among the knowledge elements (McEvily and Chakravarthy 2002). The transfer of such knowledge is error prone and involves a greater risk of misinterpretation and misapplication in product innovation (Galunic and Rodan 1998). This is because deep functional knowledge limits the firm's ability to draw new conclusions and find new links among diverse pieces of knowledge. Second, deep market knowledge implies differential functional expertise in collecting and disseminating market information. This leads to different "thought worlds" (Leonard-Barton 1992), which further increase the uncertainty and ambiguity of knowledge transfer (Szulanski 1996). For these reasons, deep knowledge tends to lead to rigidities in knowledge transfer and sharing, hindering the firm's ability to assimilate knowledge. Consequently, firms develop coordinating structures to provide functional units with the means to understand and develop confidence in one anothers' analysis and interpretation (Hoopes and Postrel 1999). Thus:

> H_2: The deeper the market knowledge, the greater is the use of KIMs.

"Market knowledge tacitness" is the extent to which market knowledge is not explicit but rather is difficult to codify and communicate (e.g., Nonaka 1994). Market knowledge is tacit when people and functional units find it difficult to articulate explicitly what they know about customers and competitors and are unable to explain effectively the causal relationships between their actions and the associated outcomes. Tacitness slows the internal transfer of market knowledge because tacit knowledge cannot be fully codified and articulated even by an expert. It can be transferred from one person to another only through a long process of apprenticeship, which necessarily involves face-to-face interactions, review of successful and unsuccessful projects, and frequent advice from experts (Galunic and Rodan 1998; Szulanski 1996). As an embedded knowledge, tacit knowledge requires the development of KIMs to unearth its potential value (Madhavan and Grover 1998). Birkinshaw, Nobel, and Ridderstråle (2002) find that the degree of observability (i.e., explicitness) of technology knowledge is negatively related to knowledge integration structures. Thus:

> H_3: The more tacit the market knowledge, the greater is the use of KIMs.

"Market knowledge specificity" refers to the extent to which the firm's knowledge is tailored to the requirements of specific contexts in which it is maximally effective but loses its value in other contexts (Galunic and Rodan 1998). For example, a firm's knowledge can be related to the attitudes of a specific customer segment toward a specific product or strategy. Specific competitor knowledge may result from an in-depth analysis of the behavior, products, and strategies of a particular competitor. In both cases, the knowledge acquired is valuable only in the context of the focal firm. For example, Lenovo's knowledge of the computer market was so specific to the Chinese context that it needed to acquire IBM's personal computer division to increase its ability to compete on the global level.

Specific market knowledge is likely to be acquired and used by experienced people and experts in specific market domains. Thus, it could be argued that the transfer of such knowledge is unproblematic even in the absence of KIMs. However, we have three reasons to predict a positive effect of specific market knowledge on KIMs. First, because specific market knowledge is valuable in the context in which it has been generated, its value is highly time sensitive. Subramani and Venkatraman (2003) show that because specific market knowledge must be exploited in a timely manner, it engenders strong norms of joint decision making, a key aspect of KIMs. Second, specific market knowledge diminishes knowledge recombination, impairing timely and effective contextual use (Galunic and Rodan 1998, p. 1197). Third, specific market knowledge reflects the use of idiosyncratic routines in the collection and use of market information by different functions. As Galunic and Rodan (1998) argue, by producing specific knowledge, these routines make the transfer of knowledge to other functions difficult. These properties of specific market knowledge increase the implementation of KIMs to ensure early settlement of communication difficulties and enable timely flow and recombination of knowledge from different functional units in the product innovation process.

> H_4: The more specific the market knowledge, the greater is the use of KIMs.

Effect of Cross-Functional Collaboration on KIMs

Cross-functional collaboration refers to the degree of cooperation, the extent of representation, and the contribution of marketing, R&D, and other functional units to the product innovation process (Kahn 1996; Li and Calantone 1998; Ruekert and Walker 1987; Song, Montoya-Weiss, and Schmidt 1997). Cross-functional collaboration is intangible, volitional, and unstructured in that it reflects only the recognition by functional units of their strategic interdependence and their need to cooperate for the benefit of the organization (Galunic and Rodan 1998, p. 1198; Kahn 1996; Kahn and Mentzer 1998; Olson et al. 2001). It ensures the alignment of goals among functional units. In contrast, KIMs permit regular patterns of interactions that enable the transfer, recombination, and use of knowledge from different functions. Therefore, KIMs respond to the problem of coordinating different knowledge elements to execute complex organizational tasks.

Anecdotal evidence supports the distinction between cross-functional collaboration and KIMs. First, despite the high degree of cooperation among its functional units, Toyota established coordinating mechanisms, including standardized reporting and documentation, formalized work processes (e.g., project reviews), problem-solving meetings, and integrative leaders, to ensure knowledge sharing and integration among its different units (Sobek, Liker, and Ward 1998). Second, a study of the most innovative firms in the world indicates that two such firms, Southwest and BMW, have adopted mechanisms, such as colocation, face-to-face meetings, and standard documentation, to integrate the knowledge among members of their cross-functional teams, despite their high degree of cooperation proclivity (*BusinessWeek* 2006). The distinction of the two constructs is salient because coordinating knowledge—particularly, specialized and complex knowledge—among different units is problematic for firms, even when perfect goal congruence (or full collaboration) is established among them (Grant 1996b, p. 114).

Contingency theory offers two principal reasons that cross-functional collaboration predicts KIMs. First, cross-functional collaboration implies increased resource dependency among functional units and, thus, a greater need for enhanced information-processing capability to coordinate the acquired knowledge. As the need for sharing knowledge and other resources among functional units increases, their interdependence grows along with the volume of resource flows and increases the use of coordinating mechanisms (see Olson, Walker, and Ruekert 1995, p. 53). Thus, increased collaboration represents a critical strategic contingency for the design of coordination mechanisms (Galbraith 1973; Kumar and Seth 1998, p. 581). As Kahn and Mentzer (1998) suggest, collaboration reflects the willingness of different functional units to cooperate; yet firms need to provide structural mechanisms to put such willingness into action. Indeed, Birkinshaw, Nobel, and Ridderstråle (2002) find that functional interdependence influences the design of interunit KIMs in the firm.

Second, the transfer and flow of knowledge among interdependent units is often costly, ambiguous, and uncertain because of the diversity of functional information, backgrounds, experiences, and thought worlds. This complicates analysis and interpretation and hinders the likelihood of novel recombinations of the firm's knowledge (Galunic and Rodan 1998). For this reason, Madhavan and Grover (1998) argue that the collective knowledge of functional units constitutes only potential knowledge. As a result, Ruekert and Walker (1987, p. 6) argue that to obtain value from cross-functional interactions, "mechanisms [must] evolve to help reduce the uncertainty and ambiguity of resource, work, and assistance flows." Similarly, Garud and Nayyar (1994, p. 372) point out that firms develop integration mechanisms because of the uncertainty and ambiguity in translating embedded collective knowledge into knowledge embodied in the new product (see also Griffin and Hauser 1996, p. 209). In brief, we argue that increased functional collaboration leads to the greater use of KIMs to regulate communication flow and learning in new product projects.[2]

H_5: The greater the cross-functional collaboration, the greater is the use of KIMs.

Market Knowledge, Cross-Functional Collaboration, and Product Innovation Performance

Market knowledge. Extant research considers market knowledge the fundamental driver of product innovation performance (Atuahene-Gima 1995, 2005; Li and Calantone 1998; Moorman and Miner 1997). However, few studies have provided detailed insights into the effects of different market knowledge characteristics on product innovation performance. Market knowledge breadth engenders product innovation performance because it increases the firm's ability to make connections among disparate market information, ideas, and concepts to gain broader and insightful perspectives (Reed and DeFillippi 1990). This logic underpins the general idea about the positive role of market orientation in product innovation (Atuahene-Gima 1995, 2005; Li and Calantone 1998). A firm with broad market knowledge has heterogeneous information and understanding of customers and competitors, enabling it to design products that match the diverse needs of its customer segments. By enhancing the firm's purview of the market, broad market knowledge also increases the firm's ability to implement and execute complex tasks quickly in product innovation processes (Kogut and Zander 1992). It does this by enhancing the chances of what Prabhu, Chandy, and Ellis (2005) call "happy accidents," in which concepts from different knowledge domains are applied in unexpected ways.

A new product based on deep market knowledge limits a competitor's ability to observe and understand the whole set of distinct and interdependent knowledge elements that underlies it (Reed and DeFillippi 1990). This is because market knowledge depth reflects a complex understanding of the causal interdependencies among customer problems and requirements and potential competitor strengths and responses, thus increasing the likelihood of the emergence of new ideas that are highly unique to the firm (Galunic and Rodan 1998). As McEvily and Chakravarthy (2002) find, competitor efforts to reconstruct such a product are likely to be undermined or lead to partial and erroneous results. Prabhu, Chandy, and Ellis (2005, p. 116) also contend that knowledge depth results in superior products because it allows for the cross-fertilization of knowledge elements that increases flexibility in generating complex patterns of new knowledge.

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[2] The direction of causality can be questioned here. However, in addition to structural contingency theory, several other arguments support our interpretation. First, rational managers would invest in costly KIM processes only when they are satisfied that different functions are willing and able to collaborate. Second, rational managers know that structures such as KIMs may be ineffective in imposing collaboration, which is more of a human and social condition. Indeed, prior research suggests that an attempt to impose cross-functional collaboration through an early implementation of KIMs can yield the opposite result (Kahn 1996). Xie, Song, and Stringfellow (2003, p 233) also note that merely imposing a cross-functional structure for product innovation cannot ensure that different functional units will collaborate.

Tacit market knowledge leads to better new product performance because it allows for differences in cross-functional logics (Galunic and Rodan 1998). Prahalad and Bettis (1986) suggest that such differential logics ensure thoughtful deliberations and generate new perspectives, novel strategic alternatives, analyses, and interpretations that enhance the efficiency of the firm's innovation activities. Furthermore, tacit knowledge develops in a "community of interaction" (Nonaka 1994) and thus is highly embedded in the firm's social system. Competitors find it difficult to imitate the social context within which the focal firm develops its new products (Reed and DeFillippi 1990).

Finally, specific market knowledge enhances innovation performance because it ensures a long-term relationship with specific contexts (e.g., customer segment) that generates highly idiosyncratic insights for product innovation. This protects the new products the firm develops from imitation because competitors lack the contextual customer knowledge that went into the process. Furthermore, a new product based on specific market knowledge is more likely to be differentiated to suit the specific customer and competitor conditions (McEvily and Chakravarthy 2002).

Cross-functional collaboration. The positive effect of cross-functional collaboration on product innovation performance is well documented in the literature (see Griffin and Hauser 1996; Luo, Slotegraaf, and Pan 2006; Song and Parry 1997). The logic is that cross-functional collaboration ensures that marketing, technical, and other functional capabilities are combined to develop a product that satisfies customer needs. It accomplishes this by improving the efficiency of knowledge use and allowing for quality decision making in new product project teams (Madhavan and Grover 1998).

H_6: The greater the market knowledge (a) breadth, (b) depth, (c) tacitness, and (d) specificity, the better is the product innovation performance.

H_7: The greater the cross-functional collaboration, the better is the product innovation performance.

Mediating Effect of KIMs on Product Innovation Performance

The direct-effects arguments for the impacts of market knowledge and cross-functional collaboration on product innovation performance are persuasive. However, a careful inspection indicates that the arguments implicitly assume a role for KIMs. As we argued previously, both the KBV and contingency theory suggest that the stickiness of market knowledge and the increased information-processing demands that result from cross-functional collaboration constitute factors that determine the firm's integration mechanisms (Birkinshaw, Nobel, and Ridderstråle 2002; Galbraith 1973; Germain and Droge 1997; Kumar and Seth 1998; Thompson 1967). Indeed, the KBV suggests that it is not knowledge per se but rather its integration that ensures competitive advantage (Grant 1991, 1996a). Specifically, KIMs ensure better performance because they enhance the likelihood of finding solutions in the product innovation process by infusing the functional units with collective learning capability. Implicit in this argument is the notion that KIMs connect knowledge to performance. Because KIMs are mandated processes for learning, they provide milestones that ensure a sense of order in cross-functional knowledge sharing, use, and learning. By providing a formal structure for knowledge integration, KIMs also provide a common forum for periodic feedback, which ensures quality decision making and completeness of a project team's activities. In so doing, KIMs reduce wasteful explorations and errors in product innovation (Sheremata 2000). Thus, dimensions of market knowledge and cross-functional collaboration affect product innovation performance indirectly through their effects on KIMs. This discussion suggests the following hypotheses:

H_8: The greater the KIMs, the better is the product innovation performance

H_9 KIMs mediate the effects of market knowledge (a) breadth, (b) depth, (c) tacitness, and (d) specificity on product innovation performance.

H_{10}: KIMs mediate the effect of cross-functional collaboration on product innovation performance.

Research Methods

Sample and Data Collection

China is an ideal context for this study. The extreme complexity and dynamism of this transitional environment means that firms must confront not only the challenges of new (and often dysfunctional) competition but also collapsing capabilities (Li and Atuahene-Gima 2001). For this reason, cross-functional collaboration and mechanisms for using market knowledge in product innovation are critical for firms to sustain innovation performance. The instrument was prepared in English and then translated into Chinese. It was checked for accuracy in line with the conventional back-translation process. We pretested the instrument with 25 managers who had at least three years of business experience in China to examine the face validity and to assess informants' understanding of the survey questions. The study used a sample of 750 firms selected randomly from a mailing list of 2500 high-technology firms provided by a local consulting firm.

As with previous studies in China (Atuahene-Gima 2005; Li and Atuahene-Gima 2001), we collected the data on-site. An interviewer scheduled appointments with the marketing manager/director as a first informant, who then nominated a second knowledgeable informant. The interviewer presented the key informants with the survey questionnaire and collected the questionnaire on completion. We motivated respondents by assuring them of confidentiality and by offering a summary of the research results and a free workshop on the research findings—information that would be meaningless to them in the absence of accurate data (Li and Atuahene-Gima 2001). We received 363 usable questionnaires, for a response rate of 48%. We compared a sample of 50 participating firms with a sample of nonparticipating firms for which we had data on sales, R&D expense, and number of employees. Analyses of variance indicated no significant differences between the two groups on number of employees (F = 1.01), sales in the most recent year (F = .89), and R&D expenditure as percentage of sales (F = .98).

Of the first informants, 90% were from marketing and sales, 4% were chief executive officers/general managers, and 6% were product development managers. These informants had a mean industry experience of 8.18 years and a mean firm experience of 4.77 years. Of the second informants, 73% were product development director/managers, 9% were from marketing/sales, 11% were chief executive officers/general managers, and 7% were from R&D. These informants had a mean industry experience of 7.76 years and a mean firm experience of 4.55 years. We also examined the quality of the informants by asking them to indicate on a ten-point scale their degree of knowledge of (1 = "not at all knowledgeable," and 10 = "extremely knowledgeable") and involvement in (1 = "no involvement," and 10 = "very high involvement") product development issues in the firm. The means for the first and second informants, respectively, were 7.55 and 7.40 for the first item and 8.00 and 7.78 for the second item. Using a multigroup analysis, we obtained the following results: unconstrained confirmatory factor analysis (CFA) model for the marketing and nonmarketing groups: $\chi^2 = 2225.7$, d.f. = 1440; constrained model for marketing and nonmarketing groups with equality constraints for structural paths, variances, and covariances: $\chi^2 = 2307.6$, d.f. = 1540; $\Delta\chi^2 = 81.9$, Δd.f. = 100; $p > .10$. Given these results of tests of invariance, we pooled the data for analysis.

Measures of Constructs

Market knowledge dimensions. We measured market knowledge breadth with four items that asked respondents, for example, to evaluate their firms' market knowledge on a continuum from "limited" to "wide ranging" (Zahra, Ireland, and Hitt 2000). We measured market knowledge depth with four items that asked the respondents, for example, to evaluate their firms' customer knowledge on a continuum from "basic" to "advanced" (Zahra, Ireland, and Hitt 2000). We measured market knowledge tacitness with four items that addressed the degree to which a firm's market knowledge could be formally documented, communicated, and learned without personal experience (Szulanski 1996). On the basis of Reed and DeFillippi's (1990) work, we measured market knowledge specificity with three items that reflected the extent to which market knowledge is specific to the firm's environment.[3]

Cross-functional collaboration. On the basis of prior studies (e.g., Li and Calantone 1998), we measured cross-functional collaboration with three items that reflected the extent of cooperation among functions. For example, we asked the respondents to rate the extent to which different functional units cooperate in establishing goals and priorities for the firms' product innovation.

KIMs. Two previous studies (Zahra, Ireland, and Hitt 2000; Zahra and Nielsen 2002) informed the measure of KIMs. We used five items that addressed the extent to which a firm uses a set of formal processes (e.g., information-sharing meetings, formal analysis of projects) to capture, interpret, and integrate knowledge.

Product innovation performance. On the basis of Atuahene-Gima, Slater, and Olson's (2005) research, we measured product innovation performance with five items that asked respondents to indicate the extent to which the firm has achieved its product development objectives, such as market share and profitability.[4]

Control variables. In testing our hypotheses, we controlled for firm size and slack, which reflect the firm's resources and market power to exploit existing competencies, build new ones, and develop innovations (Chandy and Tellis 1998). To prevent skewness, we measured firm size with the logarithm of the number of employees. We measured slack with three items that tapped the availability of excess resources to fund new projects. We controlled for environmental uncertainty because the KBV suggests that knowledge integration becomes even more critical in uncertain and competitive environments (Grant 1996a). Furthermore, functional units tend to perceive higher interdependence and therefore are motivated to implement integration mechanisms in uncertain environments (Ruekert and Walker 1987). We examine two aspects of uncertainty. First, market uncertainty reflects the speed of change in customer needs and preferences and in competitor actions; we measured this with three items that cover the speed of change of customer needs and competitive conditions. Second, technological uncertainty reflects the speed of change and instability of the technology environment; we measured this with four items that tap the speed and unpredictability of technological changes.

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[3] Unlike other studies (e.g., Atuahene-Gima 2005; Li and Calantone 1998; Narver and Slater 1990) that differentiate between customer and competitor knowledge, we take a holistic measurement approach to the concept of market knowledge. Because the characteristics of knowledge we describe here are the same for customer and competitor knowledge, we did not have any theoretical rationale to expect differential effects of customer and competitor knowledge on KIMs. Thus, to reduce the complexity of the model and the burden on our informants, we chose a more aggregated measure of market knowledge.

[4] We took steps to ensure that respondents did not confuse this measure of the achievement of the firm's product innovation objectives with its overall performance. We measured overall firm performance relative to competitors with eight items: return of sales, growth in profit, return on assets, sales growth, market share growth, cash flow, overall operational efficiency, and reputation for performance. We performed three discriminant tests for product innovation performance and firm performance. First, a CFA two-factor solution yielded the following: $\chi^2 = 351.20$, d.f. = 64. When we constrained them into one factor, we obtained the following: $\chi^2 = 773.30$, d.f. = 65. Therefore, we have a significant change in chi-square of 422.10 (d.f. = 1, $p < .000$), suggesting discriminant validity. Second, we performed discriminant tests using Fornell and Larcker's (1981) approach. The average variance extracted for both product innovation performance (.72) and firm performance (.71) was greater than the squared correlation between them (.66). Finally, the correlation between product innovation performance and firm performance was .81, with a standard error of .02. The two-standard-error confidence interval for this correlation estimate is between 77 and .85. Because it does not include 1, discriminant validity is demonstrated (Anderson and Gerbing 1988).

Finally, we controlled for the degree of radicalness of the firm's product innovation activities to capture the firm's learning capability, which influences propensity for knowledge sharing and product innovation outcomes (see McGrath 2001). We measured product innovation radicalness with three items that assessed the newness of the firm's innovation activities in terms of, for example, customers targeted and products offered. The Appendix presents all the measures and their sources.

Assessing the Reliability and Validity of Measures

We performed an exploratory factor analysis with Varimax rotation for data we obtained from both types of informants. Both the first and the second informants' responses resulted in 11 factors with eigenvalues greater than 1, accounting for 68.58% and 68.50% of the total variance, respectively. For both informants, all the items loaded cleanly on the expected factors, without significant cross-loadings. Then, we tested the measurement model for both informants with a CFA, using AMOS 6.0. All the items loaded significantly on the expected constructs, indicating convergent and discriminant validity of the measures. The fit indexes showed that the model fit the data reasonably well for both the first (χ^2/d.f. = 1.56, goodness-of-fit index [GFI] = .87, comparative fit index [CFI] = .94, and root mean square error of approximation [RMSEA] = .04) and the second (χ^2/d.f. = 1.43, GFI = .88, CFI = .95, and RMSEA = .03) informant. In each case the constructs had acceptable levels of reliability, average variance extracted (AVE), and discriminant validity.[5]

Next, we submitted data from the two informant groups to two multigroup analyses to assess the invariance of the measurement model. First, we specified a model in which we constrained factor loadings, variances, and covariances in the two groups to be equal and compared it with a baseline model with no equality constraints, using a chi-square difference test (Byrne 2001). The results suggested the absence of significant differences in factors loadings, variances, and covariances (unconstrained model: χ^2 = 2153.11, d.f. = 1440; constrained model: χ^2 = 2218.32, d.f. = 1540; $\Delta\chi^2$ = 65.21, Δd.f. = 100; $p > .10$). Second, we assessed the invariance of items and latent variables means between the two groups. Following Steenkamp and Baumgartner's (1998) guidelines, we first compared the raw score means for each single item with a one-way analysis of variance and found no statistically significant differences between the two informant groups ($.22 < F < .99$). Then, we estimated two CFA models in which the latent variable means were first freely estimated and then constrained to equality (Sörbom 1974). The results suggested the absence of significant differences in latent variable means between the two groups of respondents (unconstrained model: χ^2 = 2602.04, d.f. = 1478; constrained model: χ^2 = 2607.84, d.f. = 1489; $\Delta\chi^2$ = 5.80, Δd.f. = 11; $p > .10$). This indicates that the pattern of factor loadings and the latent variables' means, variances, and covariances do not differ significantly across the two groups. As further evidence of consistency between the two informant groups, we computed the interrater agreement index (r_{wg}) for each measure (James, Demaree, and Wolf 1984). For constructs measured on the five-point scale, the index ranges from –1 to 1, indicating minimum and maximum agreement respectively.[6] The lowest r_{wg} index for the whole set of items was .83, indicating a high level of agreement between the two informant groups (see the Appendix).

Given these results, we ran a third CFA on the combined items for the two informant groups. This model performed reasonably well (χ^2/d.f. = 1163.2/720 = 1.62, GFI = .86, CFI = .94, and RMSEA = .04; see the Appendix). On the basis of Fornell and Larcker's (1981) work, we tested for discriminant validity of the constructs by examining whether the square root of the AVE of each construct (shown in the diagonal in Table 1) was greater than the highest correlation between latent variables involving the focal construct (shown above the diagonal in Table 1). Market knowledge breadth had slightly weak discriminant validity. As a fallback, we followed Bagozzi, Yi, and Phillips's (1991) recommendation and examined whether a one-factor model fit the data better than the hypothesized two-factor model for each pair of constructs involving market knowledge breadth. In each case, the chi-square of the constrained one-factor model was significantly greater than the chi-square for the unconstrained two-factor model, suggesting discriminant validity.[7]

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[5] The exceptions were the AVEs for KIMs and market knowledge breadth for the second informant group, which were slightly below the highest squared correlation with the other latent variables, indicating weak discriminant validity. For these two constructs, we performed an additional test based on the work of Bagozzi, Yi, and Phillips (1991). In all cases, the two-factor model fit the data better than the constrained one-factor model. Detailed results of these analyses are available on request

[6] For the seven-point scale adopted for product innovation performance, $-1.25 \leq r_{wg} \leq 1$.

[7] The results were as follows: market knowledge breadth versus market knowledge depth (unconstrained model: χ^2 [d.f.] = 138.26 [19]; constrained model: χ^2 [d.f.] = 279.28 [20]; $\Delta\chi^2$ [Δd.f.] = 141.02 [1]), market knowledge breadth versus market knowledge specificity (unconstrained model: χ^2 [d.f.] = 79.08 [13]; constrained model: χ^2 [d.f.] = 461.05 [14]; $\Delta\chi^2$ [Δd.f.] = 381.97 [1]), market knowledge breadth versus market knowledge tacitness (unconstrained model: χ^2 [d.f.] = 89.83 [19]; constrained model: χ^2 [d.f.] = 544.78 [20]; $\Delta\chi^2$ [Δd.f.] = 454.95 [1]), market knowledge breadth versus cross-functional collaboration (unconstrained model: χ^2 [d.f.] = 96.33 [13]; constrained model: χ^2 [d.f.] = 250.23 [14]; $\Delta\chi^2$ [Δd.f.] = 153.90 [1]), market knowledge breadth versus KIMs (unconstrained model: χ^2 [d.f.] = 238.20 [26]; constrained model: χ^2 [d.f.] = 488.29 [27]; $\Delta\chi^2$ [Δd.f.] = 250.09 [1]), market knowledge breadth versus technology uncertainty (unconstrained model: χ^2 [d.f.] = 95.89 [19]; constrained model: χ^2 [d.f.] = 525.09 [20]; $\Delta\chi^2$ [Δd.f.] = 429.20 [1]), market knowledge

TABLE 1
Correlation Matrix and Descriptive Statistics of Measures

	1	2	3	4	5	6	7	8	9	10	11	12
1. Market knowledge breadth	.70	.70	.09	.07	.57	.58	.47	.23	.17	.45	.54	N.A.
2. Market knowledge depth	.56	.71	–.01	.04	.62	.53	.41	.19	.06	.43	.35	N.A.
3. Market knowledge tacitness	.07	–.02	.78	.23	11	.18	.07	.31	.23	.03	.12	N.A.
4. Market knowledge specificity	.06	.04	.24	.77	.20	.02	.15	.17	.27	.31	.20	N.A.
5. KIMs	.49	.51	.10	.20	.69	.62	.43	.30	.13	.54	.34	N.A.
6. Cross-functional collaboration	.44	.42	.12	.04	.53	.72	.27	.10	.03	.36	.39	N.A.
7. Product innovation performance	.41	.41	.04	.11	.39	.26	.86	.23	.17	.35	.24	N.A.
8. Technological uncertainty	.19	.19	.28	.14	.28	.12	.20	.75	.58	.19	.26	N.A.
9. Market uncertainty	.18	.08	.24	.22	.13	.07	.14	.49	.73	.22	.40	N.A.
10. Organizational slack	.38	.38	.02	.25	.45	.34	.31	.18	.19	.80	.36	N.A.
11. Radical innovation	.42	.29	.11	.17	.29	.31	.19	.22	.32	.31	.73	N.A.
12. Firm size	.07	.12	–.04	–.17	.06	–.02	.24	–.01	–.02	.07	–.03	N.A.
Number of items	4	4	4	3	5	3	5	4	3	3	3	N.A.
M	3.69	3.60	3.39	3.03	3.59	3.65	4.60	3.33	3.33	3.32	3.40	4.73
SD	.60	.58	.76	.84	.68	.61	1.08	.74	.69	.76	.71	1.5
Skewness	–.14	–.04	–.31	–.01	–.64	–.17	–.52	–.16	–.26	–.30	–.09	.55
Kurtosis	.61	.00	–.05	–.45	.69	–.02	.22	–.20	–.01	–.12	–.06	.07

Notes: The diagonal elements are square roots of the AVE. The upper-right triangle elements are the correlations among the latent variables (φ). The lower-left triangle elements are correlations among the composite measures (unweighted mean of the items for each construct). N = 363, except for firm size, which is N = 351. N.A = not applicable.

Given these results, we used the average of the responses of the two informants for all the remaining analyses to reduce the potential for common method variance (Slater and Atuahene-Gima 2004). Table 1 reports descriptive statistics and correlations among the study variables. Note that we measured product innovation performance on a seven-point scale. This provides a different psychological frame to the informants compared with the other variables measured on five-point scales, thus hindering common method bias.

Analysis and Results

Direct Effects

We used regression analysis to test the direct effects of market knowledge characteristics and cross-functional collaboration on KIMs and product innovation performance. As Table 2 (Model 1) shows, market knowledge breadth (b = .16, $p < .01$), market knowledge depth (b = .20, $p < .01$), market knowledge specificity (b = .13, $p < .01$), and cross-functional collaboration (b = .31, $p < .01$) have a positive and significant effect on KIMs. These results support H_1, H_2, H_4, and H_5. The effect of market knowledge tacitness on KIMs is not significant; thus, H_3 is not supported.

The results in Model 2 show that market knowledge breadth (b = .26, $p < .01$), market knowledge depth (b = .18, $p < .01$), and market knowledge specificity (b = .09, $p < .05$) have positive and significant effects on product innovation performance, whereas the effect of market knowledge tacitness is not significant. These results support $H_{6a, b, d}$ but not H_{6c}. Cross-functional collaboration is unrelated to product innovation performance; thus, H_7 is not supported. Among the control variables, organizational slack (b = .16, $p < .01$) and technology uncertainty (b = .16, $p < .01$) are positively related to KIMs, but only firm size is related to product innovation performance (b = .21, $p < .01$).

Mediating Effect of KIMs

We followed the three-step regression procedure that Baron and Kenny (1986) recommend to examine the mediating role of KIMs. As we showed previously, market knowledge breadth, depth, and specificity have positive and significant effects on product innovation performance. Furthermore, all dimensions of market knowledge, except for tacitness, and cross-functional collaboration are positively related to KIMs. When KIMs are entered into Model 3 (Table 2), it shows a positive and significant effect on product innovation performance (b = .14, $p < .05$), in support of H_8. The inclusion of KIMs leads to a slight decrease in the effect size of market knowledge breadth (from .26 to .24) and of market knowledge depth (from .18 to .15), but both remain significant, suggesting partial mediation. The effect of market knowledge specificity on product innovation performance was not significant, suggesting full mediation.

Recall that market knowledge tacitness and cross-functional collaboration are unrelated to product innovation performance. Testing for mediation for these variables violates Baron and Kenny's (1986) first test condition. However, several recent studies in various fields of research have argued that this constraint may be relaxed without hamper-

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breadth versus market uncertainty (unconstrained model: χ^2 [d.f.] = 86.16 [13]; constrained model: χ^2 [d.f.] = 355.42 [14]; $\Delta\chi^2$ [Δd.f.] = 269.26 [1]), market knowledge breadth versus organizational slack (unconstrained model: χ^2 [d.f.] = 77.78 [13]; constrained model: χ^2 [d.f.] = 395.53 [14]; $\Delta\chi^2$ [Δd.f.] = 317.75 [1]), market knowledge breadth versus innovation radicalness (unconstrained model: χ^2 [d.f.] = 83.75 [13]; constrained model: χ^2 [d.f.] = 260.34 [14]; $\Delta\chi^2$ [Δd.f.] = 176.59 [1]), market knowledge breadth versus product innovation performance (unconstrained model: χ^2 [d.f.] = 193.21 [26]; constrained model: χ^2 [d.f.] = 535.17 [27]; $\Delta\chi^2$ [Δd.f.] = 341.96 [1]).

TABLE 2
Results of Regression Analysis: Standardized Path Coefficients (t-Values)

	KIMs	Product Innovation Performance	
Independent Variables	**Model 1**	**Model 2**	**Model 3**
Control Variables			
Organizational slack	.16	.10	.08
	(3.38)**	(1.94)	(1.53)
Radical innovation	–.02	–.05	–.04
	(–41)	(–.87)	(–.83)
Firm size	.04	.21	21
	(1.05)	(4.52)**	(4.42)**
Technology uncertainty	.16	.08	.06
	(3.52)**	(1.43)	(1.00)
Market uncertainty	–.07	.03	.04
	(–1.45)	(.49)	(.66)
Main Effects			
Market knowledge breadth	.16	.26	.24
	(3.13)**	(4.40)**	(3.99)**
Market knowledge depth	.20	.18	.15
	(3.88)**	(3.08)**	(2.58)**
Market knowledge tacitness	.01	–.01	–.01
	(.13)	(–.26)	(–.27)
Market knowledge specificity	.13	.09	.07
	(3.00)**	(1.79)*	(1.43)
Cross-functional collaboration	.31	.04	–.01
	(6.73)**	(.73)	(–.07)
Mediating Effect			
KIMs			.14
			(2.19)*
F value	30.82**	14.78**	14.02**
R^2	.48	.30	.31
Adjusted R^2	.46	.28	.29
ΔR^2			.01
F change			4.80*

*$p < .05$ (one-tailed test for hypotheses, and two-tailed test for control variables).
**$p < .01$ (one-tailed test for hypotheses, and two-tailed test for control variables).
Notes: N = 351.

ing the validity of the mediation analysis (see Preacher and Hayes 2004, p. 719; Shrout and Bolger 2002, pp. 429–30; Smith, Collins, and Clark 2005, pp. 354–55).[8] Specifically, Sobel's (1982) test enables the investigation of indirect effects for independent variables, regardless of the significance of their total effects on the dependent variable. With the exception of market knowledge tacitness, Sobel's test indicated significant, indirect effects for market knowledge breadth (b = .04, t = 1.71, $p < .05$), market knowledge depth (b = .05, t = 1.86, $p < .05$), market knowledge specificity (b = .02, t = 1.71, $p < .05$), and cross-functional collaboration (b = .08, t = 2.06, $p < .05$), in support of $H_{9a,\ b,\ d}$ and H_{10} but not of H_{9c}.

Structural Equation Modeling

We examined the robustness of the preceding results with structural equation modeling (SEM). The first model (SEM1) examined the direct effects of the independent variables on product innovation performance with the path from KIMs constrained to zero. The fit indexes (χ^2 [d.f.] = 1206.80 [751], CFI = .94, and RMSEA = .04) suggested a good fit with the data. The second model (SEM2), which involved a full mediation of the effects of the independent variables by KIMs, also showed a good fit with the data (χ^2 [d.f.] = 1228.10 [755], CFI = .94, and RMSEA = .04). Finally, based on modification indexes, a third partial mediation model (SEM 3), which allowed a direct effect of market knowledge breadth on product innovation performance, showed a good fit (χ^2 [d.f.] = 1203.50 [754], CFI = .94, and RMSEA = .04). Model comparisons with the chi-square difference test indicated that SEM3 performed better than both SEM1 ($\Delta\chi^2$ [Δd.f.] = –3.3 [3], $p > .10$) and SEM2 ($\Delta\chi^2$ [Δd.f.] = –24.6 [1], $p < .001$).

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[8] For example, Shrout and Bolger (2002, p. 429) support recommendations to set aside the first step of Baron and Kenny's (1986) approach, arguing that "[b]ecause a test of the $X \rightarrow Y$ association may be more powerful when mediation is taken into account, it seems unwise to defer considering mediation until the bivariate association between X and Y is established." Similarly, Preacher and Hayes (2004, p. 719) note several errors that could occur by strict adherence to this condition and argue that it is possible to find a significant, indirect effect even when there is no evidence for a significant, direct effect.

With the exception of a nonsignificant effect of market knowledge depth, the structural paths in SEM3 were consistent with the results we obtained using the regression analysis, and KIMs (b = .18, t = 1.70, $p < .05$) and market knowledge breadth (b = .39, t = 3.50, $p < .01$) were significantly related to product innovation performance.[9] Following Brown's (1997), Shrout and Bolger's (2002), and others' (see n. 8) recommendations, we again tested the significance of the specific mediation effects as follows: market knowledge breadth (total effect b = .85, $p < .05$; direct effect = .83, $p < .05$; indirect effect b = .03, not significant [n.s.]), market knowledge depth (total effect b = .16, n.s.; direct effect = .09, n.s.; indirect effect b = .07, $p < .10$), market knowledge specificity (total effect b = .14, n.s.; direct effect = .10, n.s.; indirect effect b = .04, $p < .10$), and cross-functional collaboration (total effect b = –.05, n.s.; direct effect = –.17, n.s.; indirect effect b = .12, $p < .10$).[10]

Overall, the results of this study suggest four conclusions: First, market knowledge specificity and cross-functional collaboration influence product innovation performance through KIMs. Second, market knowledge depth has both a direct and an indirect effect (through KIMs) on product innovation performance. Third, market knowledge breadth has a direct, nonmediated effect on product innovation performance. Fourth, product innovation performance is not influenced either directly or indirectly by market knowledge tacitness.

Discussion

Our goal in this article was to advance the marketing literature by untangling the complex relationships among market knowledge dimensions, cross-functional collaboration, KIMs, and product innovation performance. We found that market knowledge depth and specificity affect product innovation performance through KIMs. Note that though the direct effect size of KIMs on product innovation performance is small relative to the effect of market knowledge breadth, it plays the additional role of linking not only market knowledge depth and specificity but also cross-functional collaboration to product innovation performance. These results echo the view that being a sticky asset, knowledge is a contingency variable and that the design for KIMs needs to take into account the nature of the knowledge base of the firm (e.g., Birkinshaw, Nobel, and Ridderstråle 2002; Germain and Droge 1997).

We found no support for the direct, positive effect of cross-functional collaboration on product innovation performance. Instead, we found that cross-functional collaboration positively affects product innovation performance through KIMs. This is consistent with the structural contingency theory argument that increased information-processing demands that result from the interdependence of functional units determine the degree to which KIMs are adopted. Although cross-functional collaboration and KIMs are important factors in the product innovation process, as is widely reported in the marketing literature, we offer the new insight that the latter factor is the route that makes the former a more valuable resource in product innovation.

In summary, our findings imply that market knowledge specificity and cross-functional collaboration (and, in part, market knowledge depth) are only potential resources and may not be inherently valuable for product innovation performance. Being distal antecedents, their potential for enhancing product innovation performance may be realized, totally or in part, through KIMs. However, the situation appears to be more complex because the effect of market knowledge breadth on product innovation performance is direct, not through KIMs. Therefore, market knowledge breadth appears to be the most potent driver of product innovation performance among the different dimensions of market knowledge we examined herein. This finding implies that types of market knowledge may have different intrinsic properties, a nuanced insight that has not yet been recognized in extant contingency theory and in the KBV.

The nonsignificant effect of market knowledge tacitness on KIMs was a surprise because prior research has found that it increases the difficulty of knowledge transfer. The lack of a relationship between market knowledge tacitness and product innovation performance echoes the mixed perspectives pertaining to the effect of tacitness in extant research (see Galunic and Rodan 1998; Hedlund 1994; McEvily and Chakravarthy 2002). We conducted a series of post hoc moderating tests with other variables in this study but found no significant nonlinear or moderated effects of market knowledge tacitness on product innovation performance. A possible explanation for our finding may be gleaned from the work of Nonaka (1994), who argues that tacit knowledge is created by individuals and is initially shared within homogeneous "communities of interaction," such as functional units. To overcome problems of different thought worlds among such units, firms may rely on project leaders with A-shaped capabilities to "craft a unifying vision that does justice to all the disciplines represented" (Madhavan and Grover 1998, p. 4). As Griffin and Hauser (1996, p. 209, emphasis added) note, "These successful developers may have *internalized* a process that allows them to get product to market successfully." This implies that unlike other market knowledge dimensions, integration of tacit market knowledge may be achieved through the tacit skills of effective team leaders rather than through formal KIMs. This appears to explain why firms such as Toyota employ the "integrative leader" as one of the key KIMs in product development (Sobek, Liker, and Ward 1998, p. 40).

As we mentioned previously, in other contexts, scholars have argued convincingly that KIMs are moderators. We evaluated this view and found significant interaction effects only between KIMs and cross-functional collaboration (b = –.11, t = –1.95, $p < .05$) and market knowledge depth (b =

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[9] Differences between estimated coefficients in regression analysis and SEM can be due to different estimation approaches (ordinary least squares versus maximum likelihood) or because regression analysis does not account for measurement error.

[10] For indirect effects (both with Sobel's test and SEM), we report unstandardized coefficients and one-tailed significance levels. For SEM, we obtained total, direct, and indirect effects estimates and significance using the AMOS 6.0 bootstrap estimation procedure with 1000 resamples.

–.16, t = –2.93, $p < .01$).[11] These findings are contrary to expectations, but they are novel. They suggest that KIMs play not only a mediation role but also an unexpected negative moderating role.

Moorman and Miner (1997, p. 101) find that environmental "turbulence can reduce the value of shared knowledge within organizations." Although they measure shared knowledge or organizational memory more broadly, the routine component of memory and our concept of KIMs may overlap to some extent. For this reason, we tested the interaction effects of technology/market turbulence and KIMs on product innovation performance but found no significant results. A possible reason might be that we focus more narrowly on structured mechanisms for knowledge integration, whereas the concept of organizational memory included collective beliefs, physical artifacts, and behavioral routines, which may interact more strongly with environmental turbulence.

Theoretical Contributions

This study contributes to marketing theory of product innovation in five main ways. First, the direct effect of market knowledge breadth sheds new light on the importance ascribed to the concept of market orientation in product innovation and the importance that marketing theory places on broad understanding of customers and competitors (Atuahene-Gima 1995, 2005; Jaworski and Kohli 1993; Narver and Slater 1990). However, the indirect, positive effects of market knowledge depth and specificity also underscore the need for market orientation theory to embrace a more fine-grained notion of market knowledge. Without this, marketing theory is unlikely to unearth new insights into the role of market knowledge in product innovation, such as those we offer here.

Second, the results regarding the effects of market knowledge dimensions suggest that theoretical exploration of the failure of firms in product innovation should not be ascribed mainly to their failure in cross-functional collaboration, as suggested in much of the previous research and in anecdotal reports. Rather, it may be possible for firms to fail even when they have effective and efficient cross-functional collaboration, if they do not have broad, deep, and specific market knowledge. This study indicates that examining only the direct effects of market knowledge and cross-functional collaboration separately may lead to an incorrect view of their power and, thus, to erroneous implications about their role in product innovation.

Third, we clarify how and why KIMs matter in product innovation performance by showing simultaneously their mediating and moderating roles. We show that KIMs convert some market knowledge dimensions and cross-functional collaboration into product innovation performance. This new insight implies that by failing to consider the mediating role of KIMs, previous research may have assumed away the information-processing demands in product innovation and thus may have reached a premature, and perhaps overly optimistic, view of the importance of market knowledge and cross-functional collaboration in product innovation. More important, these findings suggest an important qualification of the dual tenets of KBV, namely, that knowledge is a necessary but not a sufficient condition for competitive advantage and that effective integration of knowledge is the key driver of competitive advantage. We show that KIMs play an important role in product innovation performance, as predicted by the KBV, by partially mediating the effects of market knowledge depth and by completely mediating the effects of market knowledge specificity and cross-functional collaboration on product innovation performance. In other words, and consistent with the KBV's contention, market knowledge depth and specificity as well as cross-functional collaboration may not be intrinsically valuable; their value may be realized through KIMs.

Fourth, contrary to the KBV tenet, market knowledge breath is valuable in and of itself because it has a direct, unmediated effect on product innovation performance. Thus, it is a sufficient condition for product innovation performance. These differential strengths of market knowledge characteristics suggest that the KBV understates the inherent value of some types of market knowledge. Thus, this study suggests the need for further research to focus on the explicit articulation of the types of market knowledge and the consideration of their different roles in understanding the firm's effectiveness in product innovation. Without such an approach, a more nuanced understanding of the role of market knowledge may be missed.

Fifth, given the complexity of the study context, the negative moderating effects of KIMs suggest that at high levels, they could stifle the effects of market knowledge

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[11] To test interactions with SEM, we followed the procedure that Ping (1995) suggests to build the interaction terms. First, for each pair of constructs X and Z forming an interaction, we mean-centered all their indicators x_1–x_n and z_1–z_m. Second, for each pair of constructs X and Z, we computed a single indicator that represents the latent product xz as $(x_1 + \ldots x_n)(z_1 + \ldots z_m)$ Third, we specified a model including the two focal constructs and their interaction term. The loading and error for the latent product are given by two equations:

$$\lambda_{xz} = (\lambda_{x1} + .\,.\ \lambda_{xn})(\lambda_{z1} + .\,.\ \lambda_{zm}), \text{ and}$$

$$\begin{aligned}\theta_{\varepsilon xz} = {} & (\lambda_{x1} + \ldots \lambda_{xn})^2 \mathrm{VAR}(X)(\theta_{\varepsilon z1} + .\,.\ \theta_{\varepsilon zm}) \\ & + (\lambda_{z1} + .\,.\ \lambda_{zm})^2 \mathrm{VAR}(Z)(\theta_{\varepsilon x1} + \ldots \theta_{\varepsilon xn}) \\ & + (\theta_{\varepsilon x1} + \ldots \theta_{\varepsilon xn})(\theta_{\varepsilon z1} + \ldots \theta_{\varepsilon zm}),\end{aligned}$$

for which all the terms on the right-hand side are taken from the measurement model (Ping 1995). The fit indexes for the five models containing the relevant interaction terms are as follows. KIMs × market knowledge breadth interaction (χ^2 [d.f.] = 1306.49 [823], CFI = .94, and RMSEA = .04), KIMs × market knowledge depth interaction (χ^2 [d f] = 1325.09 [823], CFI = .94, and RMSEA = 04), KIMs × market knowledge tacitness interaction (χ^2 [d.f.] = 1298.10 [823], CFI = .94, and RMSEA = .04), KIMs × market knowledge specificity interaction (χ^2 [d.f.] = 1327.92 [823], CFI = .94, and RMSEA = .04), and KIMs × cross-functional collaboration interaction (χ^2 [d.f.] = 1284.85 [823], CFI = .94, and RMSEA = .04).

depth and cross-functional collaboration on product innovation performance. It appears that though some characteristics of market knowledge and cross-functional collaboration may make KIMs necessary, the degree of KIMs must be tempered by the amount of contextual complexity the firm faces and the resulting need for functional flexibility and, perhaps, autonomy (Eisenhardt and Martin 2000). At high levels, KIMs may stifle the flexibility and creativity of cross-functional interactions and in the use of deep market knowledge (Kumar and Seth 1998, p. 583). Although previous studies in other contexts have found positive moderating roles for KIMs, the new insight we offer is that there may be a threshold of the KIM level beyond which market knowledge depth and cross-functional collaboration may have detrimental effects on performance. Thus, the use of KIMs appears to involve a trade-off between their necessity occasioned by stickiness of market knowledge and the information-processing demands of cross-functional collaboration on the one hand and the implementation costs of KIMs on the other hand. This is a trade-off that has not been uncovered in extant research.

Managerial Implications

The argument that market knowledge and cross-functional collaboration enhance product innovation performance has gained wide acceptance among practitioners. Our study supports this conclusion but also qualifies it in several ways for managers. First, our study calls on managers to consider the attributes of the market knowledge they use in new product projects to design KIMs properly. Marketing managers are fervent adherents of the market orientation tenet with respect to the value of acquiring broad and comprehensive knowledge about customers and competitors. This notion is justified given the research on the positive effects of market orientation on product innovation outcomes. However, this study digs deeper into the features of market knowledge by finding that though broad market knowledge is important, managers need to pay equal attention to deep and specific market knowledge. These dimensions of market knowledge appear to influence the design of KIMs, which in turn affect product innovation performance. Thus, the new insight for managers is that broad market knowledge is inherently valuable for product innovation performance, but emphasizing breadth over other market knowledge characteristics and integration mechanisms may be detrimental for the achievement of the full potential of the firm's new product projects. Managers need to endow new project teams with the human and financial resources to acquire and apply broad, deep, and specific market knowledge in new product development activities. In this respect, our measures of market knowledge characteristics could serve as guides for managers who want to collect and use customer and competitor knowledge in line with these characteristics.

Second, the results suggest that it is the structured knowledge integration processes that enable the translation of cross-functional collaboration into better product innovation performance. This means that managers who encourage cross-functional collaboration as an end in itself but neglect formal knowledge integration processes may not achieve their intended objectives in product innovation. Toyota provides a good example of a company that values cross-functional collaboration but takes the extra step of deploying KIMs (Sobek, Liker, and Ward 1998). Finally, managers must be creative in balancing the need for KIMs engendered by the information-processing demands of cross-functional collaboration and market knowledge and the need for functional flexibility in the collaboration and use of market knowledge. Our results suggest that KIMs are not without costs of implementation, which could trap the unwary and thus lead to less effective use of market knowledge and cross-functional collaboration.

Limitations and Future Research Directions

This study has several limitations that should be considered in the interpretations of the findings. First, we used cross-sectional data, which cannot suggest causal relationships. In particular, if the theoretical lens is organizational learning and knowledge creation, it could be theorized that KIMs are antecedents to the dimensions of market knowledge we discussed here (e.g., Zahra, Ireland, and Hitt 2000). However, our focus was on knowledge integration viewed from a structural contingency theory lens and, more specifically, on the view of knowledge as a contingency variable (Birkinshaw, Nobel, and Ridderstråle 2002; Germain and Droge 1997; Olson, Walker, and Ruekert 1995). This perspective suggests that the type of knowledge determines the nature of coordination mechanisms for knowledge integration (Galbraith 1973). Future studies based on the former lens could examine how KIMs affect the dimensions of market knowledge.

Second, the generalizability of the results is limited because we used data from a sample of firms in China. Third, extant research (Olson, Walker, and Ruekert 1995; Sobek, Liker, and Ward 1998) and contingency theory describe several integrative mechanisms (Galbraith 1973) that we did not consider here and should be investigated in further research for their ability to leverage market knowledge in product innovation. Fourth, our exclusive focus on market knowledge is a limitation, given the role of technological knowledge in product innovation. A more explicit incorporation of the nature of technological knowledge along the dimensions used for market knowledge in future studies may provide a better understanding of knowledge integration and product innovation performance.

Fifth, although we controlled for several factors that account for variance in firms' growth, market power, and technological skills (i.e., firm size, slack, environmental conditions, and radical innovation), we did not include some potentially influential covariates that have been considered in previous studies, such as industry maturity (Eisenhardt and Tabrizi 1995), company age (Sinkula 1994), and R&D strength (Li and Calantone 1998). This might limit the definitive evaluation of the relative importance of the antecedents of KIMs and product innovation performance in the current study, and it offers a chance for future researchers to take steps in this direction. Finally, two of our scales, market knowledge breadth and KIMs, did not meet the .50 threshold for AVE, suggesting the need for further scale development. In addition to alleviating these limitations, there are other fertile avenues for further research.

First, our study highlights the key role of market knowledge characteristics in enhancing KIMs and product innovation performance and underscores the central importance accorded to knowledge and its integration in the concept of market orientation. However, despite the numerous studies on market orientation, scholars are yet to recognize the distinctions among different knowledge characteristics espoused in the KBV. We argue that market-oriented firms may differ with respect to the type of market knowledge they collect and use in their product innovation processes. Thus, we suggest that two firms with the same degree of market orientation that have differential levels of market knowledge breadth, depth, tacitness, and specificity could display markedly different effectiveness in product innovation. This implies that examining the role of market orientation in product innovation without isolating and accounting for the fine details of market knowledge characteristics may lead to an incomplete understanding or even misleading results.

Second, our findings underscore the need for researchers to examine factors that may be more proximate antecedents of product innovation performance and, thus, potential drivers of the effect of cross-functional collaboration. Researchers need to move past their exclusive focus on the direct effects of cross-functional collaboration and begin to examine factors that may moderate or mediate its role in product innovation. These include different types of firm internal and external environments, such as internal commitment and competitive uncertainty (Song and Parry 1997); different managerial styles; different routines in the product innovation process, such as product standards and market definition (Dougherty 1992); different functional relationship experiences; and so forth. Indeed, with the exception of Maltz and Kohli (2000), we and other scholars in the marketing literature seem to have a positive bias toward cross-functional collaboration. However, cross-functional collaboration involves potential bottlenecks, such as functional competition, conflicts, and personality differences. Although not exhaustive, these aspects point to important opportunities for further research to provide a deeper examination of how cross-functional relationships and knowledge affect innovation.

The results of this study, along with those in previous studies, suggest that there is little understanding of the value of tacit knowledge. McEvily and Chakravarthy (2002) indicate that tacitness may involve two dimensions: characteristic ambiguity and linkage ambiguity, the former dimension being an antecedent of the latter dimension. Given the KBV's arguments that tacitness is a key factor that could erect imitation barriers to protect the firm's advantage, research is needed on whether these two dimensions apply to market knowledge and whether they offer similar or differential advantages in product innovation. Finally, further research should examine more closely the dynamic interplay between market knowledge characteristics and technological knowledge characteristics in the linkage between cross-functional collaboration and KIMs in product innovation. We believe that given the potential synergies between market and technological knowledge in product innovation, further research should tease out subtler, but still important, combined effects of the different characteristics of these kinds of firm knowledge.

In conclusion, this study challenges researchers and managers to take a more sophisticated assessment of how and why market knowledge and cross-functional collaboration affect product innovation outcomes. We believe that by delineating the differential relative effects of the dimensions of market knowledge and cross-functional collaboration and by showing the dual mediating and moderating roles of KIMs, this study illuminates in a more systematic way how such a goal can be achieved. With additional work that builds on this study and incorporates the role of technological knowledge, a more comprehensive account of the complexity of the processes by which firms develop successful product innovations can be achieved.

APPENDIX
CFA of Measures

Measure and Source	Description	Standardized Factor Loadings	t-Value	r_{wg}
Product innovation performance[a] (Atuahene-Gima, Slater, and Olson 2005)	Rate the extent to which your firm has achieved the following product development objectives:			
	•Market share relative to the firm's stated objectives.	.76	16.72	.91
AVE = .74	•Sales relative to stated objectives.	.81	18.49	.92
CR = .93	•Return on assets relative to stated objectives.	.93	23.12	.92
α = .94	•Return on investment related to stated objectives.	.93	23.09	.92
	•Profitability relative to stated objectives.	.87	20.76	.91
Market knowledge breadth[b] (Zahra, Ireland, and Hitt 2000)	Compared to major competitors, our firm's knowledge of			
	•Competitors' strategies is *narrow* vs. *broad.*	.63	12.27	.90
AVE = .49	•Competitors' strategies is *limited* vs. *wide ranging.*	.60	11.55	.87
CR = .79	•Our customers is *narrow* vs. *broad.*	.78	16.12	.90
α = .81	•Our customers is *limited* vs. *wide ranging.*	.76	15.80	.91
	•Competitors' strategies is specialized vs. general.[f]			
	•Our customers is specialized vs. general.[f]			
Market knowledge depth[b] (Zahra, Ireland, and Hitt 2000)	Compared to our major competitors, our firm's knowledge about			
AVE = .50	•Competitors' strategies is *shallow* vs. *deep.*	.68	13.40	.90
CR = .80	•Competitors' strategies is *basic* vs. *advanced.*	.62	11.80	.89
α = .82	•This firm's customers is *shallow* vs. *deep.*	.76	15.58	.90
	•This firm's customers is *basic* vs. *advanced.*	.78	16.16	.88
Market knowledge tacitness[c] (Szulanski 1996)	Market knowledge competencies are difficult to			
	•Comprehensively document in manuals or reports.	.86	19.29	.84
AVE = .61	•Comprehensively understand from written documents.	.88	19.91	.85
CR = .86	•Identify without personal experience in using them.	.68	13.93	.86
α = .86	•Precisely communicate through written documents.	.68	13.94	.84
	•There is no precise list of market knowledge skills necessary to successfully perform our activities.[f]			
Market knowledge specificity[c] (New items based on Reed and DeFillippi 1990)	Please indicate your agreement with each of the following statements with respect to your firm's market knowledge:			
	•Our knowledge of customers and competitors is quite specific to our kind of business.	.66	13.16	.84
AVE = .60 CR = .82 α = .81	•It will be very difficult for an employee to transfer market knowledge acquired in our firm to other business environments.	.86	17.74	.84
	•Our market knowledge and skills are tailored to meet the specific conditions of our business.	.79	16.23	.83
	•Our market knowledge largely depends on the human and physical assets we have dedicated to acquiring information about market conditions.[f]			
KIMs[d] (Zahra, Ireland, and Hitt 2000; Zahra and Nielsen 2002)	To what extent does your firm use each of the following activities to capture, interpret, and integrate knowledge and information about market and technology conditions?			
AVE = .47	•Regular formal reports and memos that summarize learning.	.72	14.84	.87
CR = .82 α = .83	•Information sharing meetings.	.77	16.19	.88
	•Face-to-face discussions by cross-functional teams.	.71	14.32	.88
	•Formal analysis of failing product development projects.	.60	11.70	.85
	•Formal analysis of successful product development projects.	.59	11.46	.86
	•Use of experts and consultants to synthesize knowledge.[f]			
Cross-functional collaboration[e] (Li and Calantone 1998)	In this organization different departments			
	•Cooperate fully in generating and screening new ideas for new products.	.75	14.81	.88
AVE = .52 CR = .76 α = .75	•Fully cooperate in establishing goals and priorities for our strategies.	.79	14.96	.86

APPENDIX
Continued

Measure and Source	Description	Standardized Factor Loadings	t-Value	r_{wg}
	•Are adequately represented on project teams and other strategic activities.	.61	11.52	.87
Technological uncertainty[c] (Jaworski and Kohli 1993) AVE = .56 CR = .83 α = .83	Please indicate your agreement with each of the following statements with respect to your firm's environment:			
	•It was very difficult to forecast technology developments in our industry.	.68	13.99	.83
	•Technology environment was highly uncertain.	.86	19.03	.83
	•Technological developments were highly unpredictable.	.82	17.82	.84
	•Technologically, our industry was a very complex environment.	.59	11.54	.84
Market uncertainty[c] (Jaworski and Kohli 1993) AVE = .53 CR = .77 α = .76	Please indicate your agreement with each of the following statements with respect to your firm's environment:			
	•Customer needs and product preferences changed quite rapidly.	.58	10.91	.88
	•Customer product demands and preferences were highly uncertain.	.82	15.20	.87
	•It was difficult to predict changes in customer needs and preferences.	.76	16.57	.85
	•Market competitive conditions were highly unpredictable.[f]			
Organizational slack[c] (New scale) AVE = .64 CR = .84 α = .84	Please indicate your agreement with each of the following statements with respect to your firm:			
	•We have uncommitted resources that can be used to fund strategic initiatives at short notice.	.72	14.89	.86
	•We have a large amount of resources available in the short run to fund our initiatives.	.88	19.57	.83
	•We will have no problems obtaining resources at short notice to support new strategic initiatives.	79	16.82	.83
	•We have a large amount of resources at the discretion of management to fund new strategic initiatives.[f]			
Radical innovation[e] (McGrath 2001) AVE = .53 CR = .77 α = .77	To what extent does each of the following factors describe this firm's product development?			
	•The products offered were new to the firm and the industry.	.78	15.40	.88
	•The customer or client needs served were new to the firm.	.72	14.04	.88
	•The users of the products or services were new to the firm.	.69	13.23	.87
	•The new products were based on revolutionary changes in technology.[f]			

[a] Seven-point scale (1 = "low," and 7 = "high").
[b] Five-point semantic differential scales (anchoring points in italics).
[c] Five-point scale (1 = "strongly disagree," and 5 = "strongly agree").
[d] Five-point scale (1 = "never used," and 5 = "widely used").
[e] Five-point scale (1 = "to no extent," and 5 = "to great extent").
[f] Items were dropped from the scale during the measure purification phase
Notes. CR = composite reliability.

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Jean-François Ouellet

Consumer Racism and Its Effects on Domestic Cross-Ethnic Product Purchase: An Empirical Test in the United States, Canada, and France

This study provides empirical evidence of the effects of consumer racism on domestic cross-ethnic product purchase in three countries. The model predicts that consumer racism will affect ethnic majorities' judgments of and willingness to buy products from each country's dominant ethnic minority. After a consumer racism measurement instrument is developed and validated, experiments and survey results show that varying levels of consumer racism affect consumer judgments of and willingness to buy domestic products that are perceived as being made by ethnic minorities in the three countries in which the tests took place. Moreover, the results indicate that minority-owned business performance is significantly and negatively affected in areas in which consumer racism is more prevalent. Moderators of consumer racism effects are the perceived level of interaction between consumers and the minority-owned company, a certain product-ethnicity image, and consumers' perceived importance of the outcome associated with consuming minority-owned companies' products and/or services.

Many countries have more or less distinct population sets within their borders. Some countries have historical ties to other countries that make them inherently bicultural; for example, Canada has historically had ties to both France and England, accounting for its citizens being mainly English-speaking, though a French-speaking minority makes up approximately 25% of the population. Other countries are currently witnessing the increasing growth of subcultural groups within their borders. This is the case, for example, in France, where citizens of former colonial lands, such as Algeria, are flooding in, in search of a better future. This phenomenon is also occurring in the United States, which received more than one million legal immigrants in 2002 alone. Hispanics now account for 13.3% of the total U.S. population (U.S. Census Bureau 2002). This gathering and interaction of several cultures within national boundaries, or cultural diversity, is widely acknowledged (Leibold and Hugo-Borrows 1997; Roberts and Hart 1997).

Because members of subcultural groups are also consumers, marketers have begun to demonstrate a growing interest in better serving them, which has given rise to the concept of "ethnomarketing" (Badot and Cova 1995; Pires, Stanton, and Cheek 2003; Tréguer and Segati 2003). Yet these minorities are also providers of products and services to the marketplace. The U.S. Census Bureau (1997) reveals that as many as 3 million minority-owned companies in the United States made up 15% of the 20.8 million nonfarm companies in 1997. Of these, 1.2 million companies, or four in ten, were Hispanic or Latino owned. This represents a new reality for consumers in countries such as France, the United States, and Canada, who are faced not only with the option of buying foreign versus domestic goods and services but also with the choice between the domestic offering of their own ethnic group or that of another.

There are many examples in the services sector. In Montreal, which is home to the largest open-air food market in North America, Marché Jean-Talon, consumers can choose from a variety of shops and stands offering flavors from Asia, Europe, and South America. A consumer looking for olive oil may choose an Italian Canadian grocer over, for example, a Chinese Canadian grocer, but how does a consumer decide where to shop for a plain steak when Marché Jean-Talon offers a choice of Mexican, Moroccan, Italian, and French Canadian butcher shops? Consider the following scenario:

> In New York City, 30-year-old Caroline must go out to fetch milk for tomorrow's breakfast. Within easy walking distance of her apartment building are three convenience stores, one owned and operated by a recently arrived Mexican immigrant named José, another by a third-generation French immigrant named Jean-Pierre, and a third one owned and operated by a Caucasian American, Vietnam veteran named Pete.

Current literature on cross-cultural marketing and consumer behavior provides some indication of which shop Caroline is likely to patronize. Intuitively, ethnocentrism (Shimp and Sharma 1987), patriotism (Bilkey and Nes

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1982), and animosity (Klein, Ettenson, and Morris 1998), all combined with a certain product-country image or country-of-origin effect (Papadopoulos and Heslop 1993), might explain Caroline's choice to walk over to Pete's shop to get her pint of milk. For example, perhaps Caroline is ethnocentric and believes in the supremacy of "white American businesses." Maybe she holds feelings of animosity toward the French for not supporting (indeed, openly criticizing) the United States in its decision to go to war with Iraq. Alternatively, if she holds stereotypes of Mexico and Mexicans' attitudes toward "fiesta," she may infer that the Latino-owned store is "less seriously" managed and question the freshness of the milk available there.

Although such attitudes may be considered socially undesirable, this may be how Caroline actually feels. Although most of those widely studied constructs have not yet been studied in within-country settings, even though they are among the most popular areas of research in marketing—for example, country of origin is the object of more than 700 published articles (Papadopoulos and Heslop 2002)—it is intuitive to conclude that these variables should exert some influence within country borders as well. The literature has studied how subcultural groups (i.e., groups within a given country, probably better labeled "subnational" groups) differ in their evaluations of third-country products (e.g., Klein, Ettenson, and Morris 1998). For example, it has been demonstrated that French Canadians evaluate French products more favorably than English Canadians do (Laroche et al. 2003). Are phenomena such as ethnocentrism and animosity the only factors likely to affect consumer behavior when it comes to buying domestic products that originate from other ethnic groups? Although it has not been extensively studied in a marketing or consumer behavior context, the popular and academic literature suggests another potentially significant influence: consumer racism (CR).

Considering that immigration is growing steadily in the United States and other countries and considering the resultant increasing importance of minority-owned companies in these economies, understanding the attitudes and behaviors of these countries' ethnic majority toward the idea of buying from minorities should hold significant importance for stakeholders, including companies, governments, and even consumers themselves. At the same time, confirming the existence and understanding the effects of such factors as CR should help minority-owned companies know if they should and how to adapt important activities, such as marketing communication, branding, and product portfolio. The implications are also potentially important for majority-owned companies and may suggest the need for adaptation in the partnerships they pursue, the distribution channel they select, and so on. For governments, the conclusions of this research could suggest a need to provide support to minority-owned companies to compensate for racial discrimination by consumers or the need to raise public awareness. Understanding how CR influences behavior differentially from neighboring constructs such as ethnocentrism and animosity should help better focus these stakeholders' attention on these influential phenomena.

To address these critical issues, this article proposes to test the existence of CR in three different country settings through the development and validation of a scale. The studies first develop the concept of CR and then test its discriminant validity. The effects of CR on consumers' judgments of products and on their willingness to buy these products are then investigated. Drawing the link between consumer behaviors and their impact on company and brand performance, a study of minority-owned companies is conducted to show how CR in their given markets affects their performance. Finally, conclusions and implications for managers and academics are discussed.

CR and How Ethnic Majorities Purchase Domestic Products

Introducing the Concept of CR

At the subnational level, the concept of CR has been postulated as an alternative explanation of animosity-like phenomena (Ouellet 2005). Wilson (1973, p. 32) defines racism as "an ideology of racial domination or exploitation that (1) incorporates beliefs in a particular race's cultural and/or inherent biological inferiority, and (2) uses such beliefs to justify and prescribe inferior or unequal treatment for that group." However, contemporary authors concur that the original biological foundation of racism has given way to bases characterized by real or imagined differences between ethnic groups in terms of their languages, cultures, customs, and lifestyles (Taguieff 1988). Thus "neoracism," or "modern racism," has apparently shifted its object from race to culture, or ethnic belonging (Gilroy 1991). In other words, racism is no longer related to race but rather to ethnicity.

Racism is often the reaction of ethnically dominant groups to ethnic minorities' "imposition" of their unassimilable cultures, which the dominant group perceives as posing a threat to the accomplishments of history, the order of things, national identity, and its supposed unity (Potvin 2000). It is always defined as having two major functions: demarcation and legitimization of domination (Memmi 1994, p. 106). Thus, by definition, racism is always directed from a dominant ethnic group toward one or more dominant minority groups. For example, in the United States, research suggests that because it is threatening to white hegemony for blacks to have influence and authority, many whites are either consciously or unconsciously motivated to find ways to perpetuate the existing imbalance of power by reacting negatively to blacks in high-status positions (Dovidio and Gaertner 1981; Knight, Giuliano, and Sanchez-Ross 2001).

Overt evidence of racism has decreased in recent years (e.g., Dovidio and Gaertner 1991, 2000), but it remains robust in more subtle forms that people may be hesitant to express (Gaertner and Dovidio 1986; McConahay 1986). These subtle forms of racism may be expressed in ambiguous situations in which behavior can be justified by motives other than racism. For example, the effects of subtle racism have been observed in people's decisions about whom to hire for employment (Dovidio and Gaertner 2000; McConahay 1983) and how personnel evaluations are conducted

(Knight et al. 2003). Thus, in general, researchers believe that racism today manifests itself more indirectly and in more symbolic ways (Myers 1993; Potvin 2000).

One example of the indirect or symbolic expression of racism might be found in consumer attitudes and behavior toward shops, goods, and/or services. Although it is not documented in the scope of racism or through evaluations of products per se, the academic literature provides hints of the influence of CR on evaluations of shops and/or products. Following a review of the literature, Whittler (1991) concludes that despite methodological limitations, some white viewers were not affected by the presence of black actors in advertisements (as measured by several factors, including brand name recall, attitude toward the product and brand, and purchase intentions), whereas others did not react as positively toward black actors as they did toward white actors.

I propose that the concept of CR—defined as the antipathy toward a given ethnic group's products or services as a symbolic way of discriminating against that group—affects consumer behavior in the domestic marketplace. I propose that CR can affect consumers' decisions to buy and their product judgments.

> P_1: CR is negatively related to (a) judgments of and (b) willingness to buy products that are perceived as originating from the dominant minority ethnic group.

Differentiating Animosity, Ethnocentrism, and CR

From ethnocentrism to ethnic ethnocentrism. Ethnocentrism is a construct defined as cross-cultural that has been operationalized cross-nationally. In the field of marketing, it is defined as the beliefs that consumers hold about the appropriateness, indeed morality, of purchasing foreign-made products in lieu of locally made products (Shimp and Sharma 1987). Consumer ethnocentrism involves consumers' tendency to exhibit a positive, or favorable, predisposition toward products that originate from their own country and to reject imported products. For nonethnocentric consumers, foreign products should be evaluated on their own merit and on the basis of the utility and benefits they provide rather than on the basis of where they were manufactured or assembled. The consequences of consumer ethnocentrism include overestimation of the quality and value of domestic products (or underestimation of the virtues of imports), a moral obligation to buy domestic products, and an intense preference for domestic products.

First coined by the sociologist William Graham Sumner in the late nineteenth century, ethnocentrism is the viewpoint that a person's ethnic group is the center of everything, against which all other groups are judged. In marketing, however, the definition and operationalization of the concept have been made with countries as their objects, never with ethnicity. Indeed, consider the scenario in which a Mexican immigrant to the United States is asked what he or she thinks of the statement "It is not right to purchase products manufactured outside the United States, because it puts Americans out of jobs." Perhaps the immigrant feels no ethnocentrism at all as an American citizen; on the contrary, this respondent may feel better about buying Mexican-made products because it helps his or her family live a good life in Mexico. So when presented with the statement "It is not right to purchase products manufactured by non–Mexican Americans, because it puts Mexican Americans out of a job," this very same person might adhere more closely to the idea, perhaps because he or she identifies more closely with the Mexican American group than with a more generic American identity. In the same way, French Canadians—the majority of whom live in the Canadian province of Quebec and who are known for their elevated nationalistic sentiments, as two referendums on secession since 1980 have shown—may exhibit much higher levels of agreement with a statement such as "French Canadians who purchase domestic products made by English Canadian companies are responsible for putting their fellow French Canadians out of work" than with a same statement that would replace "French Canadians" with the more generic "Canadians."

An important contribution to consumer research has been the CETSCALE, which enables the measurement of ethnocentrism across countries (Shimp and Sharma 1987). Studies of consumer ethnocentrism have consistently shown scores on the scale to correlate inversely with willingness to buy imports, cultural openness, income, education, and perceptions of the quality of imported goods (Netemeyer, Durvasula, and Lichtenstein 1991; Sharma, Shimp, and Shin 1995; Shimp and Sharma 1987). The scale has demonstrated consistency across several countries (Netemeyer, Durvasula, and Lichtenstein 1991) but never across ethnic groups within a given country. I postulate the existence of ethnic-based ethnocentrism, which would have the same antecedents, effects, and correlates as Shimp and Sharma's (1987) ethnocentrism, only at the subnational, cross-ethnic level, which may serve as an alternative explanation of CR-like phenomena.

From national animosity to ethnic-based animosity. Recent research has focused on examining whether hostile attitudes toward a specific foreign country affect attitudes toward products from that country. Klein, Ettenson, and Morris (1998) introduce the concept of animosity, defined as the remnants of antipathy related to previous or ongoing military, political, or economic events. They hypothesize that feelings of animosity toward a specific country, as distinct from consumer ethnocentrism, affect consumers' willingness to purchase foreign products rather than their judgments or evaluations of those products. They find evidence to support this in a study of consumers' willingness to buy Japanese products in the Chinese city of Nanjing, where 300,000 people were massacred by the Japanese in World War II. Although Klein, Ettenson, and Morris find that animosity toward a country affects willingness to purchase products in an extreme case—namely, the Chinese in Nanjing—an interesting question that Nijssen and Douglas (2004) raise is whether animosity has the same influence under less extreme conditions.

Another question pertains to animosity defined at the subnational level. Although Klein, Ettenson, and Morris (1998) operationalize the construct in a cross-national setting, the factors that influence animosity on a between-country level may also be valid within a given country. For example, Tibetans may have remnants of (if not active) antipathy toward the Chinese because of prior military events, such as the invasion of Tibet. Some French Canadians may be antipathetic to English Canadians because of what they perceive as previous institutionalized political and economic domination aimed at assimilating them. Latino Americans may exhibit remnants of antipathy toward white Americans because of current perceived exclusion from well-paying professional positions. Algerian immigrants to France may not have forgiven the French for the ill-treatment of civilians during the French–Algerian war of the 1950s. Already, animosity between the Alte Länder (former West Germany) and Neue Länder (former East Germany) has been demonstrated to affect consumer behavior in the easternmost part of Germany (Hinck 2004).

I further postulate that ethnic-based animosity affects consumers' purchase behavior in the domestic marketplace distinctly from and independently of CR. Indeed, CR and animosity are different constructs according to the literature. Although animosity appears to refer to a (currently or formerly) dominated group's antipathy toward its (current or former) "dominator," CR goes the other way around. Moreover, CR is rooted in a dominant group's inability to impose its (cultural) domination, whereas animosity seems to be rooted in a dominated group's antipathy toward the dominating group, potentially because of the latter's efforts to impose its (cultural) domination. Most important, animosity is defined and has been demonstrated not to be related to consumers' beliefs about product quality. However, racism, and thus CR, suggests the legitimization of domination. Therefore, it is expected that racist consumers express less favorable judgments of products that originate from the ethnic group against whom they hold racist feelings. A Mexican American exhibiting animosity toward Americans may refrain from buying white American products even though he or she believes that they are of great quality, in accordance with Klein, Ettenson, and Morris's (1998) findings. However, a white American customer exhibiting CR toward black Americans may downgrade his or her evaluation of the latter group's products *and* refrain from buying anything from that group, in accordance with racism literature (Memmi 1994). Finally, methodological reasons also justify keeping both concepts distinct. Although animosity may be somewhat "acceptable" in society, racism, and thus CR, is not, which makes it difficult to measure (Saucier and Miller 2003).

Three distinct yet easily confused constructs emerge from the preceding discussion. In summary, ethnic-based ethnocentrism, animosity, and CR theoretically differ on three fundamental bases: their object, their effects, and their social desirability. First, animosity and CR are postulated to be specific to an ethnic group—that is, directed at one specific ethnicity—whereas ethnic-based ethnocentrism is postulated not to be—that is, directed at all but a person's own ethnic group. Second, ethnocentrism and CR are postulated to affect consumer evaluations of products *and* willingness to buy products, whereas animosity has been demonstrated to affect only willingness to buy. Third, ethnocentrism and animosity are not known to correlate significantly with social desirability, based on previous studies. Therefore, it is expected that consumers will still be open to stating their level of ethnocentrism and animosity but will be less open to admitting their level of CR, a more socially undesirable construct.

Given the different natures, antecedents, and effects as detailed in the literature, CR is expected to be distinct from the constructs of ethnocentrism and animosity and, thus, to have differential effects (see Table 1). Therefore, a person could be ethnocentric and racist in addition to holding feelings of animosity, the effects of which are cumulative:

TABLE 1
Differential Effects of Ethnic-Based Ethnocentrism, Ethnic-Based Animosity, and CR

Variable	Directionality	Effects
Ethnic-based ethnocentrism	From either ethnic group toward itself	Increased judgments about products from own group and decreased judgments about products from all other groups. Increased willingness to buy products from own group and decreased willingness to buy products from all other groups. (Shimp and Sharma 1987)
Ethnic-based animosity	Ethnic group specific (apparently from the ethnic minority toward the ethnic majority)	Decreased willingness to buy products from the majority ethnic group. No effect on product judgments. (Klein, Ettenson, and Morris 1998)
CR	Ethnic group specific (from the ethnic majority toward the dominant ethnic minority)	Decreased judgments about products from the dominant ethnic group. Decreased willingness to buy products from the dominant ethnic group.

P_2: Ethnic-based ethnocentrism, ethnic-based animosity, and CR emerge as different and distinct constructs at the subnational, cross-ethnic level.

Moderators of CR

Given the previous findings in the racism literature that suggest that the construct is somewhat evasive, identification of potential moderators of CR on judgments of and willingness to buy products perceived as originating from the dominant minority was undertaken. Indeed, general racism literature has not yet pointed to any moderator of the effects of racism on general beliefs, attitudes, or behavior. Therefore, potential moderators were identified on the basis of three qualitative surveys conducted in Grenoble, France, in Montreal, Canada, and in Boston, Mass.

A questionnaire that measured ethnic affiliation, ethnic ethnocentrism, animosity, and general racism toward the dominant ethnic minority (Arabs in France, French Canadians in Canada, and Hispanics in the United States) was first administered to potential informants recruited through a street-intercept procedure.[1] In Boston, of 152 passersby, 70 agreed to complete the screening questionnaire (63 of 87 in Grenoble and 70 of 141 in Montreal). Of the 70 respondents, 33 were rated as being affiliated with the dominant ethnic group, low on ethnocentrism, low on animosity, and high on racism on the basis of a cutoff of 3 out of 7 (41 in Grenoble and 35 in Montreal). This cutoff point was established through a pretest of the scales, which revealed a median of approximately 3 for the three scales. Thirty prequalified informants agreed to take part in the qualitative study in Boston (22 in Grenoble and 20 in Montreal). To generate content for a topic that is sensitive to social desirability, a projective "third-person" technique was used in which respondents were presented with a scenario and asked to describe beliefs, attitudes, and behaviors that could be adopted by a racist individual in such situations. The interviews lasted 45 minutes on average. Content analysis was performed and suggested three potential moderators of the effects of CR on product judgments and willingness to buy.

Level of interaction (LoI). In its general sense, the term "product" usually refers to a bundle of both tangible and intangible attributes. According to the American Marketing Association, a product can be an idea, a physical entity (a good), a service, or any combination of the three (Bennett 1995). Through their varying level of tangibility, products also require a varying LoI with other human beings. Mainly intangible products (or services) typically require more interaction between customers and sellers because of the inseparability of production and consumption (Zeithaml, Parasuraman, and Berry 1985). Yet extant racism literature mentions that racists typically tend to avoid close contact with groups against which they hold racist feelings (Gaertner and Dovidio 1986; McConahay 1983; Memmi 1994). Therefore, the higher the level of cross-ethnic interaction required to buy, use, or dispose of the product, the more salient the negative effects of CR should be. As one informant in Boston stated, "I care less about buying their products than having to actually be in contact with them in stores. They're so lazy; they just exasperate me." In other words, CR should have a greater effect on consumers' judgments of and willingness to buy services than on their judgments of and willingness to buy goods that are perceived as originating from dominant ethnic minorities. This is convergent with approach–avoidance theory (Donovan and Rossiter 1982; Mehrabian and Russell 1974) and servicescape models (Bitner 1992; Tombs and McColl-Kennedy 2003).

P_3: An increase in the level of cross-ethnic interaction that the product requires increases the effects of CR on (a) product judgments and (b) willingness to buy.

Product-ethnicity image (PEI). In international consumer behavior literature, product-country image effects refer to the extent to which the national origin of a particular product influences its evaluation (Papadopoulos and Heslop 1993; Peterson and Jolibert 1995). Product-country image may interfere with ethnocentrism in circumstances in which an ethnocentric consumer, who views buying foreign-made products as immoral, is faced with the purchase of products whose foreign origin (Italian designer shoes, Japanese cameras, French wine, American burgers) suggests better quality than domestic-made products in the same categories (Balabanis and Diamantopoulos 2004). Thus, it is postulated that the same construct at the ethnic level—PEI—could influence reluctant racist consumers' evaluations of and willingness to buy products in categories for which they believe ethnic groups are more capable than their own. Even racist consumers are likely to admit that French citizens of Northern African origin probably make the best couscous or that Latino American–owned restaurants likely serve the best enchiladas in Los Angeles. As one Bostonian explained, "What would [a racist] guy buy from Latinos? Chile con carne." Therefore, the negative bias of racist consumers' judgments of and willingness to buy the products of the dominant ethnic minority should be moderated by more favorable PEI.

P_4: A more favorable PEI decreases the effects of CR on (a) product judgments and (b) willingness to buy.

Importance of outcome (IoO). Another variable that seems to moderate informants' willingness to buy (but not product judgments) is the importance they attribute to outcome. Research has shown that for relatively unimportant products, consumers are willing to forgo even unfavorable product-quality evaluations due to country of origin in making their purchase decisions (Ahmed et al. 2004). Conversely, for important products, stereotypes such as country of origin and probably CR exert significant influence on both product evaluations and purchase intentions (Hong and

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[1] Measurements were made using adapted versions of (1) Kim, Laroche, and Lee's (1989) multidimensional index of ethnicity for ethnic affiliation, (2) the CETSCALE (Shimp and Sharma 1987) for ethnocentrism, (3) the economic dimension of Klein, Ettenson, and Morris's (1998) scale for animosity, and (4) Saucier and Miller's (2003) subtle racism scale for racism.

Wyer 1989). This phenomenon has also been postulated as an explanation of marketing researchers' difficulties in linking product judgments with purchase intentions or behavioral variables (d'Astous and Ahmed 1992). As a French informant revealed,

> [North Africans] never put as much effort into what they're doing as [ethnic white] French So when it's about washing a car, doing laundry, or serving food, you can live with having to deal with a [North African], even though you know it won't be perfect, but if it's something serious, like surgery or managing savings, then no way.

In other words, racist consumers may be more inclined to buy products from dominant ethnic minorities despite negative product judgments if these products have little importance to them.

> P_5: An increase in consumers' perceived IoO (a) does not affect product judgments but (b) increases the effects of CR on willingness to buy.

Multistudy Scale Development Program

Given the lack of a consumer behavior–focused measurement instrument for racism in a marketing context (i.e., CR), the studies reported herein focused on developing and testing a reliable and valid scale to measure CR. Development of a scale was necessary for several reasons. First, the most widely used measure of racism, McConahay, Hardee, and Batts's (1981) modern racism scale, is not directly relevant to the study of consumer behavior. It was not developed for such a purpose and thus contains items with little or no relevance to the study of consumer behavior or marketing (e.g., "Blacks have more influence upon school desegregation plans than they ought to have"). Other available racism scales also share this problem (Saucier and Miller 2003). Second, available scales are directed at blacks, and the applicability of such scales to ethnic groups has not yet been demonstrated. Third, the widely used modern racism scale appears to be correlated with social desirability (Dunton and Fazio 1997; Fazio et al. 1995), making its use less than comfortable. Finally, the intention behind this research was to provide a measure that could be used in multiple settings, regardless of the majority and minority groups. A review of the literature provides no evidence that any of the existing racism scales can be applied to other countries or cultures.

For these reasons, development and validation of a specific CR scale was undertaken in three different countries. According to the previously cited definitions, for racism and, thus, for CR to take place, the presence of a majority ethnic group alongside an ethnic minority that is (or is at least perceived to be) unassimilable is required. Thus, it was decided to operationalize this investigation in three countries that present such a setting: the United States, Canada, and France.

The Hispanic and Latino subpopulation is the dominant ethnic minority in the United States. The growth of this subpopulation has given rise to fears that English may be "overtaken" by Spanish as the main language in many parts of the country, leading to the founding of movements seeking to make English the official language of the United States (DeMasters 1999). Organizations such as U.S. English have been formed to urge states and Congress to enact official English and English-only laws that would encompass all aspects of government. Many states, including Alabama, California, Arizona, and New Jersey, have already adopted English-language laws. At the same time, Latinos and English speakers in the United States do not enjoy the same standards of living. The U.S. Census Bureau (2002) reports an important discrepancy between the incomes of Hispanics and non-Hispanic whites; 21.4% of the former live in poverty compared with 7.8% of the latter. It has been suggested that racial discrimination directed toward Latino and Asian immigrants is the underlying motivation for such English-language laws and is a factor that explains income discrepancy (Bender 1996; PBS 1997). The Boston area, with more than 85,000 Hispanics and Latinos accounting for 14.4% of its population and with nonwhites accounting for 43.2% of its population (U.S. Census Bureau 2000), was deemed to be a pertinent city in which to conduct this multistudy research program.

Because of its linguistic duality and within-country differences, Canada was also deemed to be an appropriate society for this multistudy investigation. Prior research in marketing provides strong evidence of the existence of two distinct ethnic groups within Canada, an English majority and a dominant French minority (e.g., Heslop, Papadopoulos, and Bourk 1998; Kim, Laroche, and Lee 1989; Kindra, Laroche, and Muller 1994; Plummer 1977; Schaninger, Bourgeois, and Buss 1985). It is widely recognized that English and French Canadians possess different cultural traits, customs, language, and traditions that yield differences in their behavior as consumers (Laroche et al. 2000). Most important, research has demonstrated that some English Canadians exhibit a certain level of racism toward French Canadians (Potvin 2000). In addition, Canada has several other ethnic minorities that allow for comparison and validation with additional ethnicities. The Montreal metropolitan area, in which the English-speaking majority and the French minority live side by side, thus resulting in more salient cross-ethnic effects, was chosen as the Canadian city in which to implement this investigation.

Finally, there has been an influx of North African immigrants in France over the past few decades, mainly from former colonies, such as Algeria, Morocco, and Tunisia. The dominant Caucasian majority lives alongside a growing "Maghrébine" (i.e., North African) minority. Approximately 3.5 million North Africans live in France, 1.5 million of whom came from Algeria, 1.3 million of whom came from Morocco, and 500,000 of whom came from Tunisia (Hervieu-Léger 2001). As in the United States and Canada, racism, and thus CR, also seems to be a factor in France; it is directed by the dominant ethnic white French community against the North African minority (Commission nationale consultative des droits de l'homme 2005). The southern French city of Grenoble, a growing technopolis that is home to an important North African community, was selected as an appropriate setting for this multistudy program.

Study 1: Item Generation and Refinement

To generate the initial pool of items for the CR scale, two main sources of information were used: a review of relevant literature and the previously described interviews with people believed to have above-average racist sentiments. Two bilingual (French and English) judges performed thematic analysis of the responses, and the results were pooled with concepts emerging in the literature, providing an initial set of 43 items.

A first test of these items was conducted with a group of six marketing faculty and doctoral students across all three countries to evaluate the content validity of the items. Judges were presented with a written definition of CR. They were then asked to rate each concept as being clearly representative, somewhat representative, or not representative of CR. In line with the work of Bearden, Netemeyer, and Teel (1989) and Zaichkowsky (1985), items evaluated as clearly representative of CR by four judges and no worse than somewhat representative by two more judges were retained. This process resulted in a set of 16 items for further analysis.

Study 2: Item Reduction and Reliability Testing

This stage involved scale purification and reliability testing for the 16 items. Data were collected directly on a laptop computer, thus limiting social effect bias. Respondents were recruited through street and mall intercepts in Boston, Montreal, and Grenoble. Of 2872 people queried (1024 in Boston, 989 in Montreal, and 859 in Grenoble), usable answers were gathered from 1090 people (335, 301, and 454), resulting in a 38% response rate. Only members of the dominant ethnic group were included in the sample; this was determined on the basis of a multidimensional index of ethnicity (Kim, Laroche, and Lee 1989), which employs language usage and ethnic identification as reliable measures of the strength of ethnic affiliation. Overall, slightly more than half of the respondents were female (57% overall; 56% in Boston, 58% in Montreal, and 56% in Grenoble), and the average annual income was US$35,000–US$50,000 in Boston and CA$35,000–CA$50,000 in Montreal. In France, it is preferable to question respondents about their socioprofessional category rather than their income, so most respondents declared being employees (42%), working class (14%), or management (13%). Typical respondents had taken some college courses, and 23% had a college or postgraduate degree (25% in Boston, 24% in Montreal, and 22% in Grenoble), closely following state, provincial, or national norms in all cases.

All items were scored using a five-point Likert format; higher scores represented greater levels of CR. Before data analysis, the Kaiser-Meyer-Olkin test of sampling adequacy and the Bartlett test of sphericity were used to determine the appropriateness of factor analysis. The Kaiser-Meyer-Olkin levels were superior or equal to .921 for all three samples, and the significance of all three Bartlett tests indicated that factor analysis was appropriate for the data. Because the CR construct was assumed to reflect a single latent person variable, it was considered most appropriate to test for a general factor on which most of the items would load positively. Thus, separate exploratory principal components factor analyses were performed on the set of 16 items for all three samples, revealing in each case a first unrotated factor that had an eigenvalue greater than or equal to 6.42 and no other factor with an eigenvalue greater than 1.0. To increase homogeneity and in the interest of developing a more parsimonious scale, items that did not have corrected item–total correlations greater than .40 were deleted, resulting in the deletion of 7 items (the same 7 items in all three samples). Follow-up factor analyses on the remaining items as well as Cattell's scree plot criterion indicated in each sample that only one factor should be retained, suggesting a 9-item, unidimensional scale.

Study 3: Confirmatory Factor Analysis

A second survey was conducted to generate data for confirmatory factor analysis. Again, the survey involved street and mall intercepts in Boston, Montreal, and Grenoble, using the same preconditions for participation and a similar laptop-based instrument. The number of usable questionnaires in all three cities was 138, 144, and 125, respectively (for a 36% overall response rate). The demographics of this second sample were similar to those achieved in the first study.

Measurement invariance across countries was first examined, in line with the work of Steenkamp and Baumgartner (1998). The scale exhibited configural invariance but only partial metric invariance across the three countries. Factor loadings of Items 3 and 5 were slightly higher in the United States, and Item 2 was slightly higher in France. Therefore, a series of confirmatory models was examined on a country-by-country basis and was estimated using LISREL 8. Examination of item reliabilities, Lagrange-multiplier tests, and tests of alternative confirmatory factor analysis models did not suggest the deletion of additional items and provided a good fit for the data in all countries (average comparative fit index = .97, and average normed fit index = .93). The chi-square statistic of the single-factor model was not significant and represented a significant improvement over any of the competing null, two-, three-, four-, and five-factor models that were examined. The coefficient alpha estimate of internal consistency reliability was also acceptable, ranging from .78 in France to .81 in the United States. The nine items and their average factor loadings based on all three samples appear in Table 2.

It should be noted that such a unidimensional conception of CR is consistent with previous research on racism. Indeed, all related research appears to have considered racism a single-factor construct and used unidimensional scales to measure the phenomenon (McConahay 1983; Saucier and Miller 2003), thus making it logical for CR to be a single-dimension concept as well.

Study 4: Discriminant Validity and Relationships with Other Measures

To assess the discriminant validity of the CR scale, a survey containing this scale along with measures of two conceptually related constructs was administered by way of a laptop-based questionnaire to 92 Anglo-American students recruited on a university campus in Boston. To distinguish

CR from consumer ethnic-based ethnocentrism, as measured by an adapted version of Shimp and Sharma's (1987) CETSCALE, and economic animosity, as measured by Klein, Ettenson, and Morris's (1998) scale, it was deemed appropriate to compare CR with both measures for the purpose of confirming discriminant validity.[2]

Each measure investigated in combination with CR demonstrated acceptable levels of reliability, with internal consistency scores of .92 for ethnic ethnocentrism and .71 for animosity. In addition, CR was slightly correlated with the economic dimension of ethnic-based animosity (.11) and moderately correlated with ethnic ethnocentrism (.26), both significant at the .05 level. This is not surprising, because ethnocentrism has been shown to correlate with patriotism and other ideology-related constructs. Moreover, common method covariation (because all constructs were measured at the same time with similar seven-point Likert scales) should explain (at least partly) such correlation scores. To test for discriminant validity against the two other scales, Fornell and Larcker's (1981) and Anderson and Gerbing's (1988) recommendations were followed. Fornell and Larcker explain that discriminant validity is evidenced when the average variance extracted by each of two constructs is greater than their shared variance. Anderson and Gerbing suggest that to confirm discriminant validity for every pair of factors, a two-factor model should fit significantly better than a one-factor model. In all cases, both tests proved significant, confirming the discriminant validity of the CR scale against those of ethnocentrism and economic animosity. This provides support for P_2.

Experimental Validation of the CR Scale

To validate the scale and test the propositions further, a study was designed to test whether CR levels influence reactions to products and services that differ in their ethnic origin. It was expected that products perceived as originating from the country's dominant minority group would be subject to less favorable product judgments and lower willingness to buy than products perceived as originating from the country's dominant ethnic group.

Method

Design. The hypotheses were tested in each country using a 2 × 3 × 2 × 2 × 2 mixed design with two levels of CR (high and low), three product ethnic origins (ethnic majority group, dominant ethnic minority group, and second ethnic minority group), two LoIs (high and low), two levels of PEI (favorable and neutral), and two levels of IoO (high and low). Three ethnic groups were used to confirm the direct effect of CR toward the dominant ethnic minority group specifically. However, CR itself was not manipulated, and respondents were assigned to a high- or low-CR condition after data collection, following a median split within each country.

TABLE 2
Confirmatory Factor Analysis Results for CR Items

Item	Single-Factor Loadings
1. We should support [Dominant Minority Group] in their struggle to build their own successful businesses in this country by consuming their goods and services.	.76
2. It is easy to understand the frustration of [Dominant Minority Group] business owners in this country, who see us patronizing other stores instead of theirs.	.74
3. [Dominant Minority Group] entrepreneurs in this country have it better than they ever had it before from consumers.	.71
4. [Recent arrivals in this country]/[Generations of economic domination and discrimination] have created conditions that make it difficult for [Dominant Minority Group] to create businesses and get us to purchase their products.	.70
5. It's really a matter of some people not trying hard enough; if [Dominant Minority Group] would only try harder, their products and services could be just as good as ours, and I would then patronize their businesses as much as I patronize ours.	.72
6 Italians, Jews, and many other minorities overcame prejudice and established profitable businesses in this country. [Dominant Minority Group] should do the same.	.66
7. How much discrimination against [Dominant Minority Group]-owned businesses by consumers do you feel there is in this country, limiting their chances to grow and succeed?	.62
8. Over the past few years, [Dominant Minority Group]-owned shops and companies have gotten less business than they deserve from customers.	.58
9. Over the past few years, [Dominant Minority Group]-owned businesses have been patronized more than they deserve by consumers.	.56

Manipulation of moderators. To manipulate moderators in the study, product categories that were in line with the experimental design were identified. A pretest involving 128 business school students in all three countries was conducted to select eight relevant product categories (see the far-left column of Table 3).

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[2] The CETSCALE was adapted to reflect the ethnic dimension of ethnic ethnocentrism For example, items such as "A real English Canadian should always buy English Canadian–made products and services" and "Anglo-American products and services, first, last, and foremost" were used.

TABLE 3
Mean Product Judgment and Willingness to Buy per Experimental Cell (Pooled)

		Product Judgments			Willingness to Buy		
Product (Condition)	**Made by**	**High CR**	**Low CR**	**Pairwise**	**High CR**	**Low CR**	**Pairwise**
Wireless speakers (low LoI, low IoO, no PEI)	EM	4.64	4.63	n.s.[a]	4.63	4.64	n.s.[a]
	DEm	2.86	3.47	$p < .001$[b]	2.74	3.35	$p < .001$[b]
	2Em	3.45	3.44	n.s.[a]	3.46	3.45	n.s.[a]
Ethnic packaged goods <$2 (low LoI, low IoO, PEI)	EM	5.46	5.44	n.s.[a]	5.43	5.43	n.s.[a]
	DEm	4.20	4.27	$p < .001$[b]	4.10	4.15	$p < .001$[b]
	2Em	4.26	4.26	n.s.[a]	4.26	4.26	n.s.[a]
Wireless speakers (low LoI, high IoO, no PEI)	EM	4.64	4.64	n.s.[a]	4.63	4.62	n.s.[a]
	DEm	2.85	3.46	$p < .001$[b]	2.53	3.38	$p < .001$[b]
	2Em	3.45	3.46	n.s.[a]	3.43	3.46	$p < .01$[c]
Ethnic goods >$50 (low LoI, high IoO, PEI)	EM	5.43	5.43	n.s.[a]	5.45	5.43	n.s.[a]
	DEm	4.20	4.26	$p < .001$[b]	3.86	4.15	$p < .001$[b]
	2Em	4.25	4.25	n.s.[a]	4.26	4.25	n.s.[a]
Convenience stores (high LoI, low IoO, no PEI)	EM	4.62	4.64	n.s.[a]	4.54	4.63	n.s.[a]
	DEm	2.46	3.46	$p < .001$[b]	2.34	3.36	$p < .001$[b]
	2Em	3.46	3.45	n.s.[a]	3.44	3.46	n.s.[a]
Ethnic restaurants <$10 (high LoI, low IoO, PEI)	EM	5.43	5.45	n.s.[a]	5.43	5.42	n.s.[a]
	DEm	3.82	4.25	$p < .001$[b]	3.70	4.17	$p < .001$[b]
	2Em	4.24	4.25	n.s.[a]	4.25	4.24	n.s.[a]
Auto repair shops (high LoI, high IoO, no PEI)	EM	4.63	4.63	n.s.[a]	4.65	4.63	n.s.[a]
	DEm	2.46	3.46	$p < .001$[b]	2.12	3.36	$p < .001$[b]
	2Em	3.44	3.46	n.s.[a]	3.45	3.44	n.s.[a]
Ethnic restaurants >$75 (high LoI, high IoO, PEI)	EM	5.44	5.42	n.s.[a]	5.43	5.44	n.s.[a]
	DEm	3.80	4.28	$p < .001$[b]	3.46	4.14	$p < .001$[b]
	2Em	4.24	4.24	n.s.[a]	4.25	4.25	n.s.[a]

[a] Pairwise comparison is not significant in all countries.
[b] Pairwise comparison is significant at the .001 level in all countries.
[c] Pairwise comparison is significant in Canada only ($\eta^2 = .070$).
Notes: EM = ethnic majority, DEm = dominant ethnic minority, and 2Em = second ethnic minority. Mean CR: United States (n = 310) = 2.17, Canada (n = 302) = 2.14, and France (n = 342) = 2.23. Mean national ethnocentrism. United States = 1.82, Canada = 2.06, and France = 2.02. Mean ethnic ethnocentrism: United States = 2.78, Canada = 2.89, and France = 2.80. Mean economic animosity. United States = 1.29, Canada = 1.46, and France = 1.33. The results of all high-CR/low-CR pairwise comparisons are noted after covariates are controlled for.

Manipulation of ethnic origin of products. Manipulating the ethnic origin of products while retaining external validity was a challenge. Indeed, contrary to country of origin, within-country ethnic origin cannot be determined through "Made in" labels on goods (which typically refer to a country, not to a region or an ethnic group) or the physical location where the service is delivered. For example, ethnically distinct Flemish and Walloon goods would both be marked as "Made in Belgium" and thus could not be differentiated on the basis of their country of origin. In the same way, it is expected that if a *churrascaria* were to open on Boston's Massachusetts Avenue, its meals would be cooked locally and not flown in from Mexico each time a customer orders a steak. A clue to ethnic origin could be the company's address; for example, an organization based in Chicoutimi, in the heart of the French-speaking Canadian province of Quebec, certainly suggests French Canadian ownership. However, to cue the ethnic origin of products, the ethnicity of the brand names was manipulated. Recent literature on foreign branding—defined as the strategy of spelling or pronouncing a brand name in a foreign language—suggests that brands serve as important cues that trigger associations with specific origins (LeClerc, Schmitt, and Dubé 1994; Thakor and Pacheco 1997). Indeed, of all cultural traits, language is one of the most frequently mentioned in the extant ethnicity literature (e.g., DeVos 1975). For example, brands such as Nortique, Corlé, and Dapône would hint more strongly at an ethnic French origin than would their more English-sounding "equivalents," Nortic, Corle, and Dapon (LeClerc, Schmitt, and Dubé 1994). To signal ethnic origin of products, ethnically suggestive brand names were generated on the basis of last names found in local telephone directories and were then pretested with a sample of 34 business school students of 28 different nationalities and ethnic backgrounds recruited in an English-language international MBA program at a business school in Montreal. Names denoting high (Ms > 5.9) ethnic affiliation were selected on the basis of a scale ranging from 1 ("not specifically ethnic sounding") to 7 ("very specifically ethnic sounding"). The ethnicity of selected names was correctly identified in 99.1% of cases. Use of brand names was randomized across the study so that respondents saw a randomized brand name for each product and so that participants would not see the same brand name twice in two different product categories.

Dependent variables. The dependent variables were product judgment and willingness to buy. The former was measured along a three-item ("bad/good," "unfavorable/favorable," and "unsatisfactory/satisfactory"), seven-point semantic differential scale (Cronbach's $\alpha = .72$). Willingness to buy was assessed using a four-item, seven-point semantic scale (Cronbach's $\alpha = .87$) derived from previous studies (Klein, Ettenson, and Morris 1998); this included statements such as "I do not like the idea of owning this product" (see the Appendix).

Stimuli. Short descriptive texts for all eight selected product, service, and shop categories were developed to be identical in structure (e.g., image color and size, length of descriptive text, brand name size) and content (e.g., message style, benefits advertised). On a computer-based interface, only the brand name of the product being displayed was automatically varied at random during data collection. Stimuli had originally been developed in English and were then translated into French for the French study by two bilingual doctoral students using a translation/back-translation procedure.

Procedure. A total of 1020 respondents were recruited through random mall or street intercepts in Boston, Montreal, and Grenoble. To ensure that respondents belonged to the dominant majority group in each country, they were first screened using Kim, Laroche, and Lee's (1989) multidimensional index of ethnicity. Sixty-six respondents were turned away after this screening. After agreeing to take part in the study, respondents were taken to a laptop computer located in a nearby coffee shop and began answering the questionnaire whenever they were ready. The first screen led respondents to believe that the purpose of this study was to test the market for several products on behalf of a venture capitalist who was trying to make decisions on potential investments. They were also informed that by answering the questionnaire, they were implicitly agreeing to participate in the study.

One at a time, respondents were then shown eight products, for which they completed measurements for dependent variables. All respondents were exposed at least twice to each of three ethnic origins, which were assigned at random to product descriptions. To ensure that respondents processed the ethnic origins of products, they were asked to write down the brand name of the product they were evaluating before completing the product judgment and willingness-to-buy scales. To limit fatigue and habituation effects, the order of the seven questions pertaining to judgment and willingness-to-buy scales was randomized for each product. Evaluations of all eight products were followed by measurements of CR and a set of other covariates that consisted of national and ethnic ethnocentrism; ethnic economic animosity; and demographics, including gender, age, income, and education. Afterward, for a manipulation check, respondents also rated the LoI, PEI, and IoO associated with products on a scale from 1 ("low LoI/PEI/IoO") to 7 ("high LoI/PEI/IoO"). In addition, respondents were asked to rate ethnic affiliation of the brand name with each of the three ethnic groups used in the studies on a scale from 1 ("not affiliated") to 7 ("highly affiliated"). Finally, respondents were asked what they thought the purpose of the study was; they were then thanked for their participation and debriefed.

Analysis and Results

A total of 954 usable questionnaires were gathered—310 in the United States, 302 in Canada, and 342 in France; there were between 50 and 57 measures per experimental cell in each country. Table 3 summarizes the results (merged across all three countries), including pairwise high- versus low-CR comparisons after ethnic ethnocentrism and animosity are controlled for. In line with Steenkamp and Baumgartner's (1998) recommendations, data could not be pooled for analysis; thus, separate country analyses were completed. To simplify presentation, the results provided in Table 3 and Figure 1 are based on pooled data. However, the text emphasizes country-by-country differences.

Manipulation checks. Manipulation checks were first completed to verify the LoI, PEI, and IoO associated with products and ethnic affiliation of the brand names used in the study. A series of t-tests revealed significant differences between all relevant groups of products in each country (in all cases, $t \geq 12.90$, $p < .001$). All products were rated as expected.

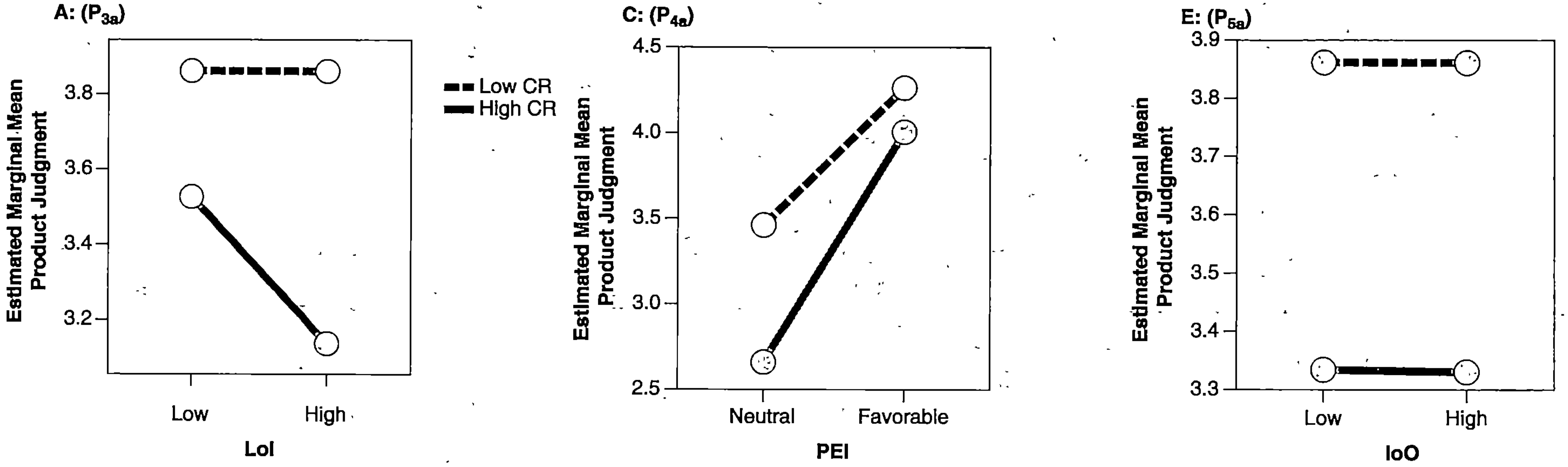
Analyses. To test the effects of CR and how they translate into acceptance/rejection of products, analyses of covariance (ANCOVAs) were conducted for each country to assess mean-level differences between racist and nonracist consumers' evaluations of and willingness to buy products with different ethnic origins. The assignment of respondents to high- and low-CR conditions was determined in each country after data collection by way of median splits; high-CR respondents belonged to the top group, and low-CR respondents belonged to the bottom group. The levels of CR (high, low) and product ethnicity of origin were set as fixed factors, and the models included all potential covariates (ethnic and national ethnocentrism, economic animosity, gender, age, income, and education). None of the sociodemographic covariates were significant, nor was national ethnocentrism. However, ethnic ethnocentrism was a significant covariate in product judgment in the United States only ($p < .05$) and had significant interaction effects with product ethnicity of origin ($p < .001$) in all samples and models. Economic animosity also significantly interacted with ethnicity of origin in the Canadian sample ($p < .05$) and in the French sample, though only marginally ($p < .10$).

The effects of CR. In line with the propositions, CR was found to interact significantly with product ethnic origin in influencing willingness to buy products that originate from dominant ethnic minorities in each country (in all samples, after covariates were controlled for, $F_{(2 \geq 2401)} \geq 111.465$, $p < .001$, $\eta^2 \geq .085$). Furthermore, CR influenced judgments about products that originate from dominant ethnic minorities in every country (in all samples, after covariates

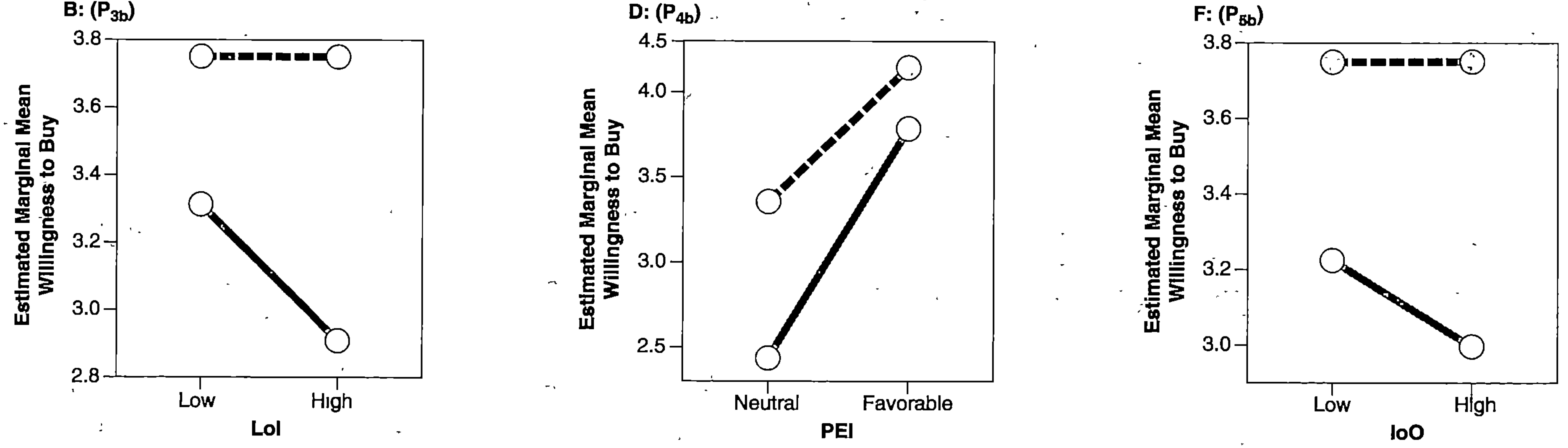
FIGURE 1

Summary of CR × Moderator Interaction Effects for Products Originating from Dominant Ethnic Minority (Pooled)

Effects on Product Judgments



Effects on Willingness to Buy



Notes: Means for high LoI are significantly different (Panels A and B). Means for PEI are significantly different in both conditions (Panels C and D). Means for high IoO are significantly different in Panel F only.

were controlled for, $F_{(2 \geq 2401)} \geq 82.384$, $p < .001$, $\eta^2 \geq .062$), confirming the difference between CR and economic animosity.[3] On average, across all three countries, high-CR respondents expressed less favorable judgments of products from the dominant ethnic minority than low-CR respondents (3.33 for high-CR respondents versus 3.86 for low-CR respondents) and lower willingness to buy (3.11 for high-CR respondents versus 3.75 for low-CR respondents). Yet in all three countries, again after ethnic ethnocentrism and economic animosity were controlled for, CR had no significant effects on judgments of and willingness to buy products that originate from the second ethnic minority group or on judgments of and willingness to buy products that originate from the dominant ethnic group, thus confirming the specific majority-to-dominant-minority directionality of CR effects.[4] This supports P_1.

Finally, direct correlation analysis between CR and age, income, education, and gender revealed absolute value Pearson correlations lower than or equal to .12 in all countries, and none reached significance at the .05 level. This suggests that CR is independent of sociodemographic factors.

Moderators of CR. Next, more thorough analyses of the identified moderators (LoI, PEI, and IoO) were conducted for each country sample by means of four-way ANCOVAs with either judgments of or willingness to buy products from the dominant ethnic minority as the dependent variable. All models used CR, LoI, PEI, and IoO as fixed factors, along with the same set of covariates used previously. All first-level interactions were computed. Again, ethnic ethnocentrism was a significant covariate in the willingness-to-buy model in the United States ($p < .05$) and in product judgments models in Canada and France (both $p < .05$). In addition, a slight interaction effect between LoI and ethnic ethnocentrism on product judgment was found in the United States ($p < .01$) and France ($p < .05$), and an interaction effect between IoO and ethnic ethnocentrism was found on willingness to buy in Canada ($p < .05$). Estimated marginal means after covariates are controlled for appear in Figure 1.

As anticipated, tests in each country revealed significant interaction effects between LoI and CR both on product judgments (in all samples, after covariates were controlled for, $F_{(2 \geq 789)} \geq 362.557$, $p < .001$, $\eta^2 \geq .477$) and on willingness to buy (in all samples, after covariates were controlled for, $F_{(2 \geq 789)} \geq 401.176$, $p < .001$, $\eta^2 \geq .504$). When CR was low, there were no significant differences in either product judgment or willingness to buy between high- and low-LoI products, after ethnic ethnocentrism and economic animosity were controlled for. However, when CR was high, high-LoI products resulted in lower product judgments (mean across all three countries: 3.14 versus 3.52) and willingness to buy (2.91 versus 3.31) than did low-LoI products (in all three countries, after covariates were controlled for, $p < .001$). This is in line with P_3.

P_4 postulated an interaction effect between CR and PEI. Tests of each country sample revealed weak yet significant main effects of PEI on product judgments (in all samples, after covariates were controlled for, $F_{(1 \geq 783)} \geq 49.583$, $p < .001$, $\eta^2 \geq .060$) and willingness to buy (in all samples, after covariates were controlled for, $F_{(1 \geq 783)} \geq 67.848$, $p < .001$, $\eta^2 \geq .080$). Significant CR–PEI interaction effects on product judgments (in all samples, after covariates were controlled for, $F_{(1 \geq 783)} \geq 672.861$, $p < .001$, $\eta^2 \geq .630$) and willingness to buy (in all samples, after covariates were controlled for, $F_{(1 \geq 783)} \geq 807.709$, $p < .001$, $\eta^2 \geq .672$) were also found, as expected. Specifically, when PEI was neutral, products were evaluated much less favorably by high-CR consumers than by low-CR consumers on both product judgments (in all countries, after covariates were controlled for, mean across three countries: 2.66 versus 3.46, $p < .001$) and willingness to buy (in all countries, after covariates were controlled for, mean across three countries: 2.43 versus 3.36, $p < .001$). When PEI was favorable, high- and low-CR consumers still significantly differed, but the gap narrowed, and both groups significantly increased their evaluations on both product judgments and willingness to buy (in all countries, after covariates were controlled for, $p < .001$). These results are in line with P_4.

Finally, interaction effects between CR and IoO were explored. No effects on product judgments were found in any of the countries. However, IoO significantly interacted with CR in explaining willingness to buy in all three countries (in all samples, after covariates were controlled for, $F_{(1 \geq 783)} \geq 136.121$, $p < .001$, $\eta^2 \geq .251$). Among low-CR respondents, IoO had no impact on willingness to buy (mean across three countries: low IoO = 3.76 versus high IoO = 3.75, not significant). However, among high-CR respondents, IoO had a significant impact on willingness to buy (in all countries, mean across three countries: low IoO = .22 versus high IoO = 3.00, $p < .005$). This confirms P_5.

Validation of the Impact of CR with Minority-Owned Firms

Methodology

To determine whether the effects of CR translate into consequences for business performance, a study was conducted to verify whether minority-owned firms that cater to customers in highly racist locations actually suffered in their performance. Through the use of the Boston metropolitan area Yellow Pages for ten white-dominated areas and suburbs, 78 Latino-owned companies were identified on the basis of their brand or corporate name. All companies were proximity consumer service providers (e.g., housekeeping services, dry cleaners, car repair) or shops. After all the firms were contacted by telephone, 70 agreed to take part in the study and answer several questions about demographics (e.g., number of years in operation, revenues, number of employees), information on identified moderators of CR effects, and company performance.[5] Company performance was assessed using a four-item (overall business performance, profit, sales, and market share), seven-point comparative measure scale to establish whether firms had lower/higher performance than other comparable companies in their locality (Cronbach's $\alpha = .84$). Store managers or owners self-reported firm performance. Although such a subjective measure may constitute a limitation to this study, this procedure is in line with leading marketing strategy research (e.g., Jaworski and Kohli 1993). Moreover, Morgan, Kaleka, and Katsikeas (2004) find a strong correlation between objective performance data and subjective assessments of performance by key informants, which supports the validity of subjective measures using key informants. To assess the CR level of the clientele of these companies, 870 respondents in the ten chosen localities completed the CR scale, along with ethnic ethnocentrism and economic animosity scales, all using seven-point Likert scales. Respondents were recruited through mall or street intercepts and were prequalified for local residence and for belonging to the dominant ethnic white and English-speaking majority (using Kim, Laroche, and Lee's [1989] index). After answering prequalification questions, respondents were told that they were about to take part in an academic research project and were then taken to a laptop computer to fill in the questionnaire.

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[3] Note that low partial eta-square coefficients reported for both effects appear to reflect the high sensitivity of CR effects to moderator factors (as is shown subsequently) and, thus, large unexplained variance when these moderators are not taken into account.

[4] The only exception was for willingness to buy wireless speakers from the second ethnicity in Canada (see Table 3)

Analyses and Results

An ANCOVA was used to test whether CR in the locality affected firms' performance, after ethnic ethnocentrism and economic animosity were controlled for. To conduct these tests, the ten localities were first divided into groups according to their mean level of CR, with the three highest-scoring areas grouped as high-CR localities (mean CR = 2.98) and the three lowest-scoring areas grouped as low-CR localities (mean CR = 1.44). Both groups of localities contained 21 companies. Mean ethnic ethnocentrism and economic animosity were then calculated for each of the six areas and included in the model. As expected, a significant CR effect on business performance was found, after covariates were controlled for. Companies located in the three highest-CR-scoring localities revealed much lower competitive performance scores than companies located in the three lowest-CR-scoring localities (2.81 versus 4.08; $F_{(1, 38)} = 10.366$, $p < .01$, $\eta^2 = .214$).

To analyze moderator effects, shops were first divided according to LoI, PEI, and IoO on the basis of median splits using measures that company respondents provided. A new ANCOVA was then conducted with the same two covariates as before, along with (high/low) CR, LoI, PEI, and IoO as fixed factors and performance as the dependent variable. Two-way interactions were computed. A main effect of CR in the area was found ($F_{(1, 32)} = 14.755$, $p < .001$, $\eta^2 = .316$). The estimated marginal means for firm performance, after ethnic ethnocentrism and ethnic animosity were controlled for, were 4.420 in low-CR localities and 2.439 in high-CR localities. Significant interaction effects of CR with LoI ($F_{(2, 32)} = 7.752$, $p = .002$, $\eta^2 = .326$) and IoO ($F_{(2, 32)} = 5.373$, $p = .010$, $\eta^2 = .251$) were also found; high-LoI and -IoO companies suffered larger CR effects than low-LoI and -IoO firms. However, the CR–PEI interaction effect was not significant ($F_{(2, 32)} = 2.916$, $p < .069$, $\eta^2 = .154$). Lower variance in PEI than in LoI and IoO in the sample could explain this lack of significance. Overall, these results tend to reconfirm the negative effects of CR on firm performance and the moderating effects of LoI and IoO.

Discussion

The purpose of this research program was to investigate the role of CR in a cross-ethnic model of domestic product purchase. At a time when ethnic groups are becoming increasingly larger in most developed countries, the findings that the products, services, and shops of minority group origin may be negatively affected by racist feelings are of significant importance for several stakeholders, including policy makers and marketing managers of minority-owned companies. For policy makers, these results suggest that measures that support minority-owned companies could be justified, considering the prejudice these companies appear to face on the part of ethnic majorities in each of the three countries studied. Educating the public on the quality of the products and services offered by ethnic minorities also appears to be justifiable, not to mention efforts to combat racism altogether.

For marketing managers throughout the world, the results of these studies suggest the need to investigate carefully the potential existence of CR in their home markets. In countries such as the United States, Canada, and France (explicitly studied here), but also the United Kingdom, Belgium, and most other Western countries characterized by high rates of immigration, this research suggests that firms should adjust their marketing strategies to the situation in their own markets. Recommended approaches could be similar to those commonly used to overcome country-of-origin effects—namely, emphasizing or deemphasizing product ethnic origin, depending on the anticipated effects of CR by majorities (e.g., through branding strategies). However, considering that ethnic ethnocentrism also affects product judgments and willingness to buy, managers of minority-owned companies should carefully determine whether the benefits of adapting their marketing and product strategies to hide their ethnic origins and gain market share among racist consumers would actually outweigh the potential loss of market share to ethnocentric consumers in their own ethnic groups. Indeed, as a Canadian informant in this qualitative study indicated when commenting on a Canadian chain's attempt to make itself more attractive to the French Canadian minority, "I stopped patronizing Eaton's when they dropped the 's' and became just Eaton." The identified moderators of CR also suggest that minority-owned firms in areas in which CR is high could fight its negative effects on performance by putting forward a favorable PEI (when applicable), by lowering the level of perceived interaction with customers (e.g., by providing services online, home pickup/delivery by third-party companies), and by limiting the risks associated with outcome (e.g., through warranties, recommendations). For majority-owned companies, this research also highlights the risks of associating with minority-owned companies in highly racist settings when seeking to increase their share of the dominant ethnic group market. Suggestions in such cases would range from not associating with minority-owned companies at all to recommending that their partners adopt some of the risk-limiting solutions identified previously.

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[5] All items were measured with single statements: for LoI, "My business involves a high/low level of personal interaction with consumers"; for PEI, "My business relies/does not rely on specific Latino or Hispanic know-how"; and for IoO: "My business offers products and/or services that are very/not critical in our customers' lives or activities."

In addition to its practical and managerial implications, this article also contributes to scientific marketing research. Indeed, it provides a robust, internationally usable instrument for the measurement of CR and describes an empirical test of the effects of CR both at the consumer and at the firm performance levels. Nevertheless, further investigation is required to determine whether the constructs accurately reflect domestic realities, as opposed to international realities. In particular, better documentation of the antecedents and consequences of CR (but also of ethnic ethnocentrism and interethnic animosity) seems to be a promising area for future investigation. In addition, although not studied in depth here, the adaptation of product-country image and country-of-origin research at the subnational (or ethnic) level also appears promising and should be considered an area for future investigation. Overall, further research is needed to investigate the occurrence and effects of CR.

APPENDIX
The Constructs and Their Indicators

Construct	Mean Cronbach's α Across Countries
Willingness to Buy	.872
I would feel guilty if I bought this product. (WB1)	
I would never buy this product. (WB2)	
Whenever possible, I would avoid buying this product. (WB3)	
I do not like the idea of owning this product. (WB4)	
National Ethnocentrism	.854
A good (nationality) does not buy foreign products. (NE1)	
It is not right to purchase foreign products because it puts (nationality) out of jobs. (NE2)	
We should purchase products manufactured in (nation) instead of letting other countries get rich off us. (NE3)	
We should buy from foreign countries only those products that we cannot obtain within our own country. (NE4)	
Ethnic Ethnocentrism	.736
A good (ethnicity) does not buy domestic products made by other people than (ethnicity). (EE1)	
It is not right to purchase products made in (nation) by other people than (ethnicity) because it puts (ethnicity) out of jobs. (EE2)	
We should purchase (national)-made products manufactured by (ethnicity) instead of letting other people in this country get rich off us. (EE3)	
We should buy from people other than (ethnic) only those domestic products that we cannot obtain from our own people. (EE4)	
Economic Animosity	.708
(Ethnicity1) are doing business unfairly with (ethnicity2) in (country). (EA1)	
(Ethnicity1) are keeping (ethnicity2) out of good jobs on purpose in this country. (EA2)	
(Ethnicity) are unfair with us business-wise. (EA3)	
Product Judgment	.722
This product seems good. (PJ1)	
I am favorable to this product. (PJ2)	
This product seems unsatisfactory. (PJ3)	

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Getting Marketers to Invest in Firm-Specific Capital

Firms gain competitive advantage by employing marketing professionals that have developed firm-specific capital. This study argues that marketers' perceptions of the governance structure employed by the firm to protect marketer capital influence marketers' job outcomes of organizational commitment, organizational trust, job satisfaction, and intention to turnover, which in turn influence the accumulation of capital more specific to the firm. The results demonstrate (1) that a protective governance structure in which marketers are able to obtain greater rewards internally than externally on more specific or less easily transferable capital does not enhance positive job outcomes and (2) that it is through the governance structures' influence on job outcomes, not through the governance structure itself, that marketing professionals are motivated to invest in the accumulation of capital specific to the firm. These results provide insights for senior marketing managers charged with developing a governance mechanism to both retain current marketing talent and develop a more effective marketing group.

Marketing personnel are key firm resources because the capital (both more and less easily transferable) they embody enables their firm to compete.[1] For example, Procter & Gamble's (P&G's) expertise in branding is, to a fair degree, embodied in the marketers P&G employs. Although a marketer at P&G may have accumulated general brand management skills, such as understanding the metrics of brand awareness and brand recall (i.e., more easily transferable capital), it is his or her firm-specific knowledge, such as the cognitive and affective manner in which select target markets are related to P&G brands, that enables him or her to manage the brand effectively through branding campaigns, brand extensions, and so forth, and thus provides P&G with a competitive advantage. Furthermore, it is argued that marketers are unique from other functional personnel (e.g., finance, accounting, engineering) in that a greater degree of their capital is specialized to the firm because their capital evolves from tasks associated with connecting customers with the firm's market offering. As such, we believe that marketing professionals who serve in the primary revenue-generating function of the firm are tasked with accumulating firm-specific capital (e.g., knowledge of customers, products) to a greater extent than those in other functional areas, such as accounting, in which professionals are charged with accumulating more easily transferable capital (e.g., knowledge, such as generally accepted accounting principles set by the Financial Accounting Standards Board). We believe that this topic is important for senior marketing managers, given the higher level of firm-specific capital accumulation for marketing professionals and the notion that firm-specific capital is theorized to foster competitive advantage. Given the importance of the capital marketers embody, the question of why marketers accumulate specific capital is an especially important topic for the advancement of marketing theory and practice.

Because less easily transferable capital provides firms with the heterogeneous resources necessary for competitive advantage (e.g., Barney 1991; Hitt et al. 2001; Hunt 2000; Pfeffer 1994), a major challenge for senior marketing managers who are responsible for marketers is to develop a governance mechanism that will stimulate marketing personnel to accumulate capital more specialized to the firm. As Williamson (1981, 1986) theorizes, unless capital embodied in employees is specialized to a particular employer, neither the employer nor the employee has a special interest in maintaining a continuing employment relationship, thus lessening the firm's ability to retain its unique combination of resources and competitive advantage. However, as Anderson and Robertson (1995) note, the structuring of a governance mechanism to stimulate marketing personnel to invest in the acquisition of firm-specific capital (e.g., knowledge of house brands) is difficult because marketing

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[1] As we develop the arguments throughout this article, we use the terms "capital," "resources," and "assets" interchangeably; different authors have used these terms to capture the same abstract concept. Capital, resources, and assets all refer to either tangible or intangible elements that an entity can draw on for support.

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personnel are often hesitant to invest in such capital because doing so increases switching costs.

Transaction cost economics provides some insight into the structuring of governance mechanisms for the treatment of specific and general investments (Anderson and Robertson 1995; Ghosh and John 1999, 2005; Williamson 1981, 1985). However, as Anderson and Robertson (1995, p. 28) indicate, "transaction-cost analysis has concerned itself with the effects of making firm-specific investments, while saying little about the process by which parties decide to make them (Williamson 1985)." In attempting to address this limitation, Anderson and Robertson note that some marketers may be willing to invest in the accumulation of capital more specific to the firm, taking a calculated risk that their employer will not abuse the investment in such capital. The issue of abuse is a concern because marketers are embedded in hierarchical governance structures, such that a firm's attempts to safeguard specific capital embodied by marketers are suspect (given that marketer investment in such capital is to the direct benefit of the firm and reverts to the marketer only at the firm's discretion).

In addressing governance in hierarchies, Williamson (1979) argues that a contractual relationship between a buyer and a seller will be plagued with opportunistic behavior in situations in which the investment of assets specific to the relationship are necessary, but the distribution of rewards from such investments are not able to be fully determined *ex ante*. Grossman and Hart (1986) build on this research, indicating that an issue left unaddressed by transaction cost economics is that of property rights under incomplete contracting. They contend that because it is difficult to write a complete contract between a buyer and a seller (i.e., stipulating all contractual conditions) *ex ante*, a possibility exists for opportunistic behavior related to the property rights of the more dependent party. Furthermore, Grossman and Hart suggest that this argument can extend to the employer–employee relationship because many details of the tasks the employee is charged with and the rewards given are left to the employer's discretion, and therefore the employee is vulnerable to abuse because he or she is more dependent on the employer than the employer is on him or her. Thus, when considering governance and the stimulation of marketing personnel investment in more firm-specific capital, it is appropriate to begin by examining marketers' perceptions of the governance structure.

It is argued that from the marketer's viewpoint, the governance structure can be examined on the basis of how the marketer believes that he or she is valued or, in other words, the extent to which the firm is perceived as attempting to safeguard or not safeguard the marketer's capital. In a free labor market, the relative frame of reference is market-based value (i.e., what can be obtained externally). Market-based value encompasses more than merely economic rewards and can include quality of work environment, firm prestige, and so forth (e.g., the prestige of working for highly reputed marketing powerhouses, such as General Electric, Federal Express, Southwest Airlines, P&G, and Starbucks, all of which are listed by *Fortune* as the United States' most admired companies). Marketers can compare what they perceive as their internal value with what they believe they could obtain externally (e.g., through sources such as *CMO* magazine, www.salary.com, friends, and colleagues at other firms). As such, we define the perceived governance structure as marketers' perceptions of the difference in value placed on their capital by their firm relative to the value they believe they could gain from other firms. When the internal value that the firm places on capital is greater than the market value, the governance structure is protective (i.e., it is intended to safeguard the capital); when the internal value is less than the market value, the governance structure is nonprotective (i.e., it is intended not to safeguard or has the consequence of not safeguarding the capital). Thus, the governance mechanism can be viewed as ranging from highly protective to highly nonprotective (with many ranges in between the extremes).

For senior marketing managers charged with developing a governance mechanism that both retains current marketing talent and develops a more effective marketing team, a fundamental limitation of transaction cost economics is the lack of redress of the complexities of incomplete contracting in the intrafirm case. In the field of marketing, research related to specific marketing professional goals, such as job performance and knowledge acquired, has been found to be driven by job outcomes (i.e., organizational commitment, organizational trust, job satisfaction, and intention to turnover; see, e.g., Atuahene-Gima and Li 2002; Brown and Peterson 1993; Christen, Iyer, and Soberman 2006). However, in the intrafirm case, it is unclear whether marketers' perceptions of the governance structure itself or job outcomes stimulate marketers to accumulate more and less easily transferable capital, thus leaving a significant gap in the literature. In other words, from a theoretical standpoint, the governance structure implied by transaction cost economics may not fully explain the stimulation of the accumulation of less easily transferable capital. As such, building on the work of Anderson and Robertson (1995) and Grossman and Hart (1986), we argue that marketers may be willing to invest in the accumulation of firm-specific capital by taking a calculated risk that their employer will not abuse their investment in such capital when they are embedded in a relationship that has stimulated positive job outcomes. Consequently, we theorize a key mediating role of job outcomes in the governance mechanism that stimulates capital accumulation. This study attempts to contribute to the marketing literature through theory development by extending transaction cost economics under an incomplete contracting situation in the intrafirm case. At the same time, this research can advance the practice of marketing by providing insights into how senior marketing managers can better stimulate marketing personnel to invest in firm-specific capital that is central to competitive advantage.

Given that the objective of this study is to understand marketer accumulation of capital (specifically, capital that is less easily transferable), this study works to understand several key issues. First, how do marketing personnel perceive the governance structure in relation to the different types of capital they embody? Second, what job outcomes accrue under governance structures related to marketers' capital? Third, how do job outcomes influence the accumulation of less easily transferable capital (the type of capital necessary for a firm's competitive advantage) by a firm's marketing personnel?

Hypothesis Development

Marketers' Perceptions of the Governance Structure Related to Their Capital Investments

Williamson (1986) notes that employer–employee interactions require special care and attention to maintain because resources will be undervalued if they are assessed under a strict utilitarian evaluation. Furthermore, Williamson (1981, p. 563) argues that "to the neoclassical proposition that the acquisition of valued skills leads to greater compensation, transaction cost reasoning adds the following proposition: skills acquired in a learning-by-doing fashion and imperfectly transferable across employers need to be embedded in a protective governance structure, lest protective values be sacrificed if the employment relation is unwittingly severed." As such, the distinction between less easily transferable and more easily transferable elements of capital is important for human asset governance (Williamson 1981; Williamson, Wachter, and Harris 1975) and, thus, for understanding marketers' perceptions of the value of their capital investments.

The lack of well-established classification schemata for the capital that a marketing professional can embody led us to conduct field interviews and broadly search the literature on capital. The initial field interviews provided face validity for Hunt's (2000) classification schemata of firm capital at the individual marketer level. Hunt identifies four elements of intangible capital: human capital, relational capital, organizational capital, and informational capital.[2] A careful review of the conceptual definitions of these four elements of firm capital suggests that each could, in part, be embodied by marketers (and, as such, can be conceptualized at the marketer level).

Human capital is defined as the stock of business skills and knowledge of a firm's employees (Hunt 2000). Extending this conceptualization to the marketing professional level, a marketing professional's human capital can be conceptualized as his or her business skills, capabilities, education, and expertise. Relational capital is defined as the stock of a firm's relational resources, including its business relationships with customers, suppliers, competitors, government agencies, and unions (Hunt 2000). Extending this conceptualization to the marketing professional level, we argue that a marketer's relational capital can be conceptualized as his or her business acquaintances, relationships, connections, and networks both internal and external to the firm. Organizational capital is defined as the firm's policies, cultural routines, norms, and competences (Hunt 2000). Extending this conceptualization to the marketing professional level, we argue that a marketer's organizational capital can be conceptualized as his or her knowledge of the firm's policies, practices, and procedures. Finally, informational capital refers to the stock of informational or knowledge resources a firm possesses related to its products, processes, customers, and resources and to its competitors' products, processes, customers, and resources (Hunt 2000). Extending this conceptualization to the marketing professional level, we argue that information capital is a marketer's knowledge of his or her firm's products and services, customers, competitors, and industry.

Furthermore, these four elements of capital embodied in marketing personnel can be categorized on the basis of their ease of transferability; that is, human and relational capital is more easily transferable than organizational and informational capital.[3] Firms operate in many different contexts or industries, and in general, these domains do not bind human and relational capital elements. Marketers' human capital is embedded in their skills and knowledge (transferable tacit and codified) that can be transferred relatively easily from one firm to another. For example, marketers' human capital developed through the acquisition of an MBA degree, which provides analytical abilities to assist the firm in developing a competitive position in the marketplace, is easily transferable from one employer to another. Similarly, marketers' internal and external relationships can often be leveraged, regardless of the firm with which they are employed.[4] For example, when marketers change employers, they can often continue to leverage their relationships with external organizations, such as market research or advertising companies, to facilitate business on behalf of their new employer.

Alternatively, organizational and informational capital is less easily transferred from one employer to another because these capital elements are derived directly from the firm, its customers, and its competitors. Although organizational and informational capital provides a resource for competitive advantage within the operating context of a specific firm, its restriction to the contextual domain of the firm, its customers, and its competitors limits the transferability of the capital to other firms. For example, marketers' informational capital, which provides them with knowledge of a firm's products, is less easily transferred to new employers that do not offer these products or compete directly against these products. Similarly, organizational processes, such as customer relationship management, that marketers have acquired with one employer (e.g., cross-selling, up-selling, lateral-selling approaches) may not be applicable to another employer that employs a different process (e.g., lifetime value approach). More important, because informational and organizational capital elements are directly related to proprietary firm aspects (e.g., products, processes), confidentiality and/or noncompete agreements greatly limit their transferability.

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[2] Although this study's focus is on human, relational, organizational, and informational capital, we are by no means suggesting that this is a definitive set of capital elements. Rather, researchers should continue to refine and expand capital elements embodied by marketing professionals to enhance the understanding of marketers as important firm resources.

[3] Empirical support for the conceptual dichotomization of the types of capital into more and less easily transferable capital was evidenced in a pretest with marketers.

[4] Although internal relational capital is somewhat less transferable than external relational capital, it is argued that marketers can continue to rely on internal relationships after departing a firm because people develop social and professional ties that often continue despite the parties being in different firms.

For capital elements that are more easily transferable in the marketplace (i.e., human and relational capital), firms can obtain substitutes without much difficulty. For example, Capron and Hulland (1999) note that marketing personnel in many firms are trained elsewhere and that marketing expertise oftentimes can be "bought in." Similarly, marketing personnel who embody these capital elements also understand that they can easily move to attractive employment alternatives. Because more easily transferable capital can easily move from one firm to another, it is more difficult for marketers to obtain value beyond the market rate on these capital investments. However, marketers who embody informational and organizational capital are more valuable to the firm because of their more specialized capital elements. Williamson, Wachter, and Harris (1975, p. 253) argue that "incumbent employees who have received specific training become valuable resources to the firm. Employee replacement is costly, since a similarly qualified but inexperienced employee would have to acquire the requisite task-specific skills before he/she would reach a level of productivity equivalent to that of an incumbent. A premium is accordingly offered to specifically trained employees to retain their employment, although in principle a long-term contract would suffice." Similarly, Ganesan and Weitz (1996) argue that in situations in which firms have invested in the development of employee knowledge of specialized organizational systems (e.g., less easily transferable capital), such firms must find ways to prevent these specially trained employees from leaving the firm to realize a fair return on their investment. As such, it can be theorized that senior marketing managers (as acting representatives of their respective firms) will employ a governance structure that values less easily transferable capital at above-market rates, and thus marketers will believe that they are able to obtain greater value on less easily transferable capital investments than on more easily transferable capital investments because of the scarcity of such capital and its ability to assist the firm in establishing a competitive advantage. More formally stated,

> H_1: Marketers perceive the governance structure as enabling them to obtain greater value (i.e., above-market-based value) on their less easily transferable capital (i.e., informational and organizational) than on their more easily transferable capital (i.e., human and relational, for which marketers are likely to receive market or below-market-based value).

Stimulating Job Outcomes

Marketers' job outcomes are based in part on their perceptions of the governance structure. Within the field of marketing, research related to job outcomes has primarily focused on organizational commitment, organizational trust, job satisfaction, and intention to turnover (see Table 1). The importance of these job outcomes is evident in their relationships to desirable aspects of a firm's culture, such as job performance, teamwork, leadership, goal setting, cooperative behaviors, and coordination (e.g., Becherer, Morgan, and Richard 1982; Brown and Peterson 1993; Christen, Iyer, and Soberman 2006; Lucas et al. 1987).

Underlying the relationship between perceived governance structure and job outcomes is the belief that governance structure signals a firm's intentions. Williamson (1986, p. 177) argues that "analyzing the economizing of transaction costs without regard to dignity encourages the view that individuals can be considered strictly as instruments." He argues that sensitivity to human needs for self- and social esteem becomes important when analyzing labor markets. More specific, it is argued that a firm signals to marketers their importance to the firm by using a protective governance structure that enables marketers to obtain value on their capital in excess of market value. Under such conditions, marketers infer positive support and caring intentions of the firm, thus positively influencing their job outcomes (i.e., greater organizational commitment, organizational trust, and job satisfaction and decreased intention to turnover). This argument is consistent with that of Ganesan and Weitz (1996), who argue that employees who are rewarded by an organization view these benefits as indicators of the organization's commitment to them. They argue that norms of reciprocity suggest that this will increase the employee's affective attachment to the firm. This argument is also consistent with the tenet of dignity that Williamson (1986) introduces, the relationship development literature (e.g., Heide and John 1988; Jap and Ganesan 2000), and research investigating job outcomes (e.g., Darmon 1990; Ganesan and Weitz 1996; Sager 1991) and is suggestive of cooperative reward distribution, a central issue in incomplete contracting (e.g., Grossman and Hart 1986).

However, although it could be argued that marketers' perceptions of the governance structure influence their job outcomes, we argue that the relationship is more complex because of capital transferability. Specifically, credible commitments (i.e., investment in specialized capital *ex ante*) are undertaken in support of building relationships (Williamson 1983). Stable, long-term relationships are derived from reciprocal or joint commitment inputs that create a context of power symmetry that aligns participants' incentive structures while enhancing mutual confidence (Gundlach, Achrol, and Mentzer 1995). However, when parties to an exchange relationship are unequal in their commitment (thus creating a context of power asymmetry), behavioral consequences differ substantially (Anderson and Weitz 1992; Gundlach, Achrol, and Mentzer 1995; Heide and John 1988; Jap and Ganesan 2000).

Marketers' more easily transferable capital not only enables them to perform their job tasks more effectively but also enhances their overall marketability because marketers recognize that an external market exists for more easily transferable capital elements. As marketers invest in and accumulate more easily transferable capital, they enhance their job mobility, thus providing for power symmetry in the relationship (because marketers could exit the relationship just as easily as the employer could "buy in" more easily transferable capital elements, neither is heavily dependent on the other; see Galunic and Anderson 2000). In such a

TABLE 1
Representative Sample of Marketing Literature on Job Outcome Constructs

Year	Study	Journal	Organizational Commitment	Organizational Trust	Job Satisfaction	Intention to Turnover
1974	Churchill, Ford, and Walker	*Journal of Marketing Research*			X	
1978	Bagozzi	*Journal of Marketing Research*			X	
1978	Busch and Bush	*Journal of Marketing Research*			X	X
1979	Teas, Wacker, and Hughes	*Journal of Marketing Research*			X	
1982	Becherer, Morgan, and Richard	*Journal of Marketing*			X	
1983	Teas	*Journal of Marketing Research*			X	
1984	Futrell and Parasuraman	*Journal of Marketing*			X	X
1985	Hunt, Chonko, and Wood	*Journal of Marketing*	X		X	X
1985	Kohli	*Journal of Marketing Research*			X	
1986	Cron and Slocum	*Journal of Marketing Research*	X		X	
1986	Fry et al.	*Journal of Marketing Research*			X	
1987	Lucas et al.	*Journal of Marketing*			X	X
1989	Hunt, Wood, and Chonko	*Journal of Marketing*	X			
1990	Darmon	*Journal of Marketing*				X
1990	Johnston et al.	*Journal of Marketing Research*	X		X	X
1991	Jaworski and Kohli	*Journal of Marketing Research*			X	
1991	Wotruba and Tyagi	*Journal of Marketing*				X
1993	Brown and Peterson[a]	*Journal of Marketing Research*	X		X	X
1994	Siguaw, Brown, and Widing	*Journal of Marketing Research*	X		X	
1994	Singh, Goolsby, and Rhoads	*Journal of Marketing Research*	X		X	X
1997	Rich	*Journal of the Academy of Marketing Science*		X	X	X
1998	Singh	*Journal of Marketing*	X		X	
2000	Chandrashekaran et al.	*Journal of Marketing Research*	X			X
2002	Atuahene-Gima and Li	*Journal of Marketing*		X		
2002	Speier and Venkatesh	*Journal of Marketing*	X		X	X
2003	Brashear et al.	*Journal of the Academy of Marketing Science*	X	X	X	X
2003	Ramaswami and Singh	*Journal of Marketing*	X	X	X	
2004	Netemeyer, Brashear-Alejandro, and Boles	*Journal of the Academy of Marketing Science*			X	X
2006	Christen, Iyer, and Soberman	*Journal of Marketing*			X	

[a] This study is a meta-analysis.
Notes: X = construct included in study.

case, senior marketing managers who are accountable for marketing personnel and want to maintain a long-term relationship with their marketers and stimulate positive job outcomes to enhance firm performance allow their marketers to obtain market value on more easily transferable capital elements. By allowing marketers to obtain market value on more easily transferable capital (i.e., capital that is not specific to the firm's activities and, though it enhances the firm's performance, could be easily replaced), the firm signals its commitment to their marketers, thus fostering positive job outcomes.

Alternatively, marketers' investments in the accumulation of less easily transferable capital, though it enables the firm to be more effective because of its specialized resources, can also be theorized to be a credible commitment to the firm in that marketers recognize that the investment in such capital limits their external (i.e., market) value (as such, the investment in less easily transferable capital creates power asymmetry within the employer–employee relationship). Given this, the more committed party (i.e., the marketer) is vulnerable to opportunism by the less committed party (i.e., the employer), such that the less committed party is more willing to abandon the relationship and is less willing to reciprocate sacrifices that the more committed party makes (Anderson and Weitz 1992; Jap and Ganesan 2000).[5] Observing the credible commitment and wishing to maintain the employment relationship, the firm reciprocates by employing a governance structure that enables marketers to obtain greater value on less easily transferable capital elements internally than they could obtain externally (i.e., the labor market). However, given that a marketer's ability to exceed market-based value on less easily transferable capital is at a cost (i.e., prior investment in less easily transferable capital creates power asymmetry and makes the marketer vulnerable to opportunistic behavior), the positive influence on job outcomes of the governance structure for less easily transferable capital elements is mitigated. Thus:

> H_2: The association of perceived governance structure for protecting marketers' capital investments with positive job outcomes is stronger for more easily transferable capital than for less easily transferable capital.

The Influence of Job Outcomes on Capital Accumulation

As we indicated previously, job outcomes are important because of their relationship to desirable aspects of a firm's culture, such as teamwork, leadership, goal setting, cooperative behaviors, coordination, and continuity (e.g., Brown and Peterson 1993; Hunt, Chonko, and Wood 1985; Singh, Goolsby, and Rhoads 1994; Speier and Venkatesh 2002). Most important, though, is that positive job outcomes stimulate marketing personnel to invest in accumulating additional capital. However, the relationship between job outcomes and additional investments in more and less easily transferable capital is different because accumulation of less easily transferable capital increases marketers' exit barriers, whereas the accumulation of more easily transferable capital increases their marketability (see Figure 1).

Marketing personnel are constrained by limits on time, energy, and so forth, in their ability to accumulate capital. As such, marketers are faced with a continuing trade-off between accumulating more or less easily transferable capital (the accumulation of more easily transferable capital is at the opportunity cost of the accumulation of less easily transferable capital, and vice versa). For example, marketers make decisions about whether they should invest their time in acquiring general business skills (i.e., human capital) with advanced degrees (e.g., MBA) or in enhancing their understanding of the firm's policies and procedures (i.e., organizational capital). Although marketing personnel accumulate both more and less easily transferable capital, we argue that job outcomes influence the rate of accumulation of each classification differently (i.e., the magnitude of influence of job outcomes on the accumulation of more or less easily transferable capital). Building on the work of Ganesan and Weitz (1996), we theorize that positive job outcomes stimulate reciprocity in marketers to invest in capital that can provide the firm with the greatest competitive advantage (i.e., less easily transferable capital). When marketers have positive job outcomes (i.e., higher levels of satisfaction, organizational trust, and organizational commitment and lower intention to turnover), they are more willing to invest in less easily transferable capital. Their motivation to invest in less easily transferable capital is a result of their willingness to increase their exit barriers out of a sense of reciprocity due to the positive job outcomes they have experienced. Thus:

> H_3: Marketers' positive job outcomes are more positively related to the accumulation of less easily transferable capital than to the accumulation of more easily transferable capital.

The Mediating Role of Job Outcomes

Job outcomes are a direct consequence of the governance structure and are a central driver of marketer capital accumulation. Thus, we argue that job outcomes mediate the effect of marketers' perceived governance structure related to their capital accumulation.

Building on the work of Williamson (1986), we theorize that when senior marketing managers establish protective governance structures that are sensitive to human needs for self- and social esteem (i.e., providing for dignity by allowing marketing personnel to obtain value on their capital), it signals to marketers the firm's long-term intentions in the relationship, thus stimulating a marketer's positive job outcomes. In other words, a protective governance structure that provides for dignity lowers the risks to marketers that firms will act opportunistically, thus enhancing positive job outcomes. Furthermore, building on prior arguments of reciprocity, we theorize that given that the marketers' job outcomes are positive, reflective of marketers' involvement in a long-term governance structure, the influence of job outcomes on the accumulation of less easily transferable

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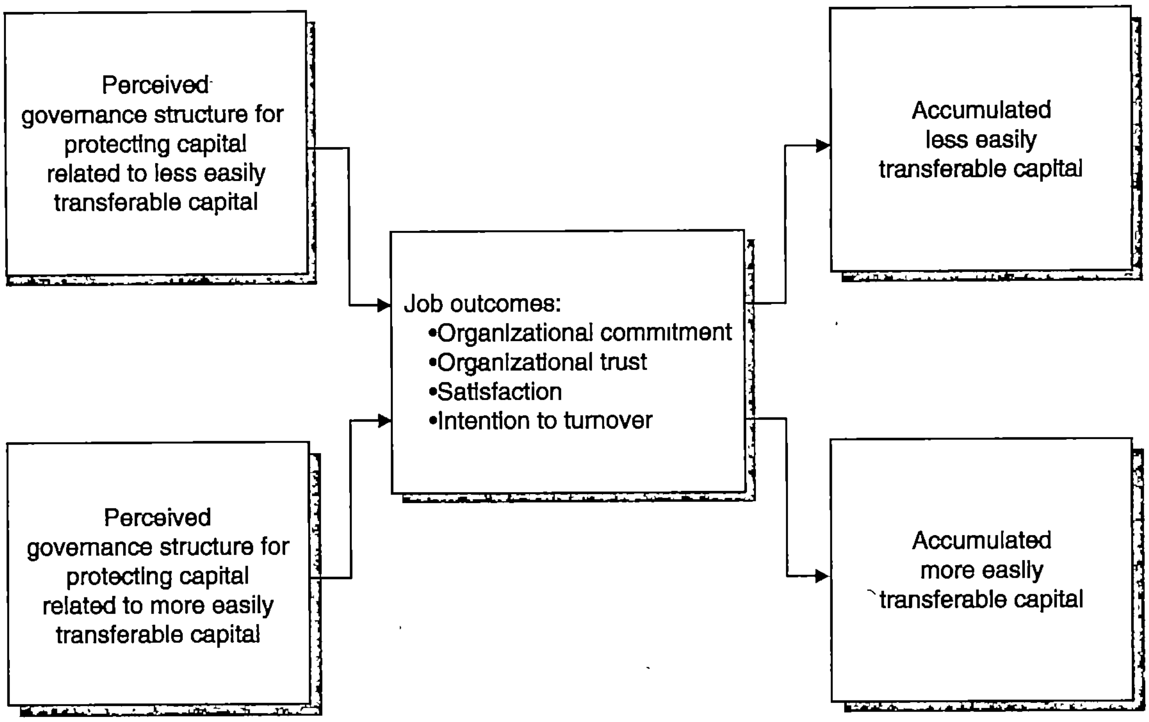
[5] Although it may be argued that symmetrical dependence exists in this case, because employers have many marketers, in general they are not as dependent on any single marketer as a single marketer is on his or her employer.

FIGURE 1
A Conceptual Model of Protective Governance Structure on Job Outcomes and Capital Accumulation


Perceived governance structure for protecting capital related to less easily transferable capital
Perceived governance structure for protecting capital related to more easily transferable capital
Job outcomes:
•Organizational commitment
•Organizational trust
•Satisfaction
•Intention to turnover
Accumulated less easily transferable capital
Accumulated more easily transferable capital

capital is greater than it is on more easily transferable capital. Thus, we theorize that job outcomes serve as a mediator between marketers' perceptions of the governance structure related to their capital and their accumulation of capital and that marketers' perceptions of the governance structure do not directly influence the accumulation of more and less easily transferable capital. More formally stated,

> H_4: Job outcomes serve as a mediator of marketers' perceptions of the governance structure related to their more and less easily transferable capital and to the accumulation of more and less easily transferable capital.

Method

We used a systematic random selection method to draw a national sample of 2000 U.S. marketing personnel registered with the American Marketing Association. We restricted the sample to subscribers to *Marketing Management*, the American Marketing Association's practitioner magazine for marketing professionals. We further restricted the sample to people in marketing roles (as opposed to education, research, or technical roles). Each survey packet was sent with a personalized cover letter and included a $1 bill to enhance response rate. Survey results were also offered to encourage response. A second survey packet was sent out at a one-month interval. There were no financial incentives in the follow-up mailing.

Of the 2000 surveys mailed, 767 surveys were returned. Thirty-four were returned undeliverable. Listwise deletion, retaining surveys that were fully completed in relation to the variables under study, resulted in 631 usable questionnaires, for an effective usable response rate of 32.1%. Respondents averaged 14 years of experience in their current profession and 39 years of age, and 46.5% (53.5%) of the respondents were men (women).

Measures

We operationalized a marketer's capital using the methodology that Churchill (1979) proposes. First, a review of the literature in the area and 15 in-depth interviews helped define the types (i.e., human, relational, organizational, and informational) and dimensions (i.e., internal value, external value, and quantity) of capital. We then sourced the literature and the interviews to generate sample items, which we then pretested with practitioners. We then analyzed and purified the sample items. Next, a pilot study (n = 157) examined the behavior of the refined measures in a subsample of the population. We assessed the results for reliability and validity and found them to meet standard benchmark criteria. We then purified the sample items.

Items used to measure the internal value, external value, and quantity of human, relational, organizational, and informational capital appear in Appendixes A through C. We operationalized each aspect of capital using a four-item, seven-point scale ranging from "strongly agree" (1) to "strongly disagree" (7); all items were reverse coded.

Subsequent to fundamental descriptive analysis, we conducted a confirmatory factor analysis (CFA) of the capital measures using AMOS 5.0 in SPSS. During CFA, items were grouped into a priori conceptualized scales. Appendixes A–C show how the 48 items were expected to load on 12 separate constructs, which consisted of four elements of capital (human, relational, organizational, and informational) across three dimensions (internal value, external value, and quantity of capital). We tested each of the four variables expected to load on each of the 12 constructs for unidimensionality and found acceptable support. Each of the 12 constructs had chi-squares with p values greater than .05, suggesting that, in general, there was no difference between the predicted and the actual correlation matrices, which is strong support for unidimensionality. In addition, each normed fit index (NFI) was greater than .90, and standardized loadings were typically in the .70–.92 range; only three loadings were below .70: EVI4 (external value, informational capital, Item 4) had a loading of .53 and a t-value of 13.07 ($p < .01$), EVO1 (external value, organizational capital, Item1) had a loading of .64 and a t-value of 16.47 ($p < .01$), and EVH3 (external value, human capital, Item 3) had a loading of .67 and a t-value of 18.05 ($p < .01$). Consequently, there was compelling evidence of acceptable unidimensionality. Furthermore, all composite reliability coefficients were greater than .60, meeting Bagozzi and Yi's (1988) guideline for acceptability.

We assessed marketers' perceptions of the governance structure first at the individual capital unit of analysis by computing the perceived internal value of each capital element less the perceived external value of each capital element (see Table 2). As such, a positive number indicates that marketers perceived a protective governance structure under which they could obtain greater value internally than they could on their capital from other firms. Next, we averaged capital elements according to transferability (i.e., human and relational capital represent more easily transferable capital, and organizational and informational capital represent less easily transferable capital) to assess marketers' perceptions of the governance structure for each classification of capital. We examined each of the derived measures for normality. All measures were within acceptable normality constraints, except for marketers' perceptions of the governance structure related to human capital. This measure presented negative skewness and high kurtosis; therefore, we log-transformed it for use in subsequent analysis.

We conceptualized job outcomes to encompass organizational commitment, organizational trust, job satisfaction, and intention to turnover. Organizational commitment refers to the marketers' psychological bond that links them to the organization and thus influences them to act in ways that are consistent with the interests of the organization (Hunt, Wood, and Chonko 1989; O'Reilly and Chatman 1986). We assessed organizational commitment with O'Reilly and Chatman's (1986) 12-item, seven-point Likert scale ($\alpha = .89$; see Appendix D).

Organizational trust refers to marketers' beliefs in the employer's honesty (i.e., the belief that one party is reliable) and benevolence (i.e., the belief that one party is genuinely interested in the welfare of the other party and is motivated to seek mutually beneficial gains; see Atuahene-Gima and Li 2002; MacKenzie, Podsakoff, and Rich 2001; Rich 1997). We assessed organizational trust with Kumar, Scheer, and Steenkamp's (1995) ten-item, seven-point Likert scale ($\alpha = .95$).

Job satisfaction refers to the emotional state or feelings resulting from the marketers' appraisals of their jobs, inclusive of pay, supervisor and coworker relationships, promotion prospects, tasks, and so forth (Bagozzi 1978; Churchill, Ford, and Walker 1974; Singh, Goolsby, and Rhoads 1994). We assessed job satisfaction with Challykoff and Kochan's (1989) four item, seven-point scale ($\alpha = .81$), anchored by "very dissatisfied" and "very satisfied."

Intention to turnover refers to when marketers intend to leave the employment of a firm before the firm is prepared to terminate the relationship (see, e.g., Busch and Bush 1978; Chandrashekaran et al. 2000; Singh, Goolsby, and

TABLE 2
Means and Standard Deviations

	M	SD
Perceived governance structure for protecting capital related to more easily transferable capital[a]	–.123	.894
Perceived governance structure for protecting capital related to less easily transferable capital[b]	.675	1.188
Perceived governance structure for protecting capital related to relational capital[c]	–.062	1.059
Perceived governance structure for protecting capital related to human capital[c]	–.185	.928
Perceived governance structure for protecting capital related to organizational capital[c]	.785	1.432
Perceived governance structure for protecting capital related to informational capital[c]	.563	1.239
Organizational commitment	4.787	1.121
Organizational trust	4.467	1.339
Satisfaction	4.482	1.327
Intention to turnover	3.505	1.930
Accumulated more easily transferable capital[d]	5.760	.857
Accumulated less easily transferable capital[e]	5.790	.902

[a] ([Internal value on relational capital + Internal value on human capital]/2) – ([External value on relational capital + External value on human capital]/2)

[b] ([Internal value on organizational capital + Internal value on informational capital]/2) – ([External value on organizational capital + External value on informational capital]/2).

[c] (Internal value of ... capital – External value of ... capital).

[d] (Quantity of relational capital + Quantity of human capital)/2.

[e] (Quantity of organizational capital + Quantity of informational capital)/2.

Rhoads 1994; Wotruba and Tyagi 1991). We assessed intention to turnover with Challykoff and Kochan's (1989) three item, seven-point scale ($\alpha = .93$), anchored by "strongly agree" and "strongly disagree." We used this scale without reverse coding, and thus it represents marketers' intentions to stay (i.e., a positive job outcome).

Next, we used CFA to evaluate the psychometric properties of the job outcome measures. The posited model fit the data acceptably ($\chi^2 = 1531.55$, d.f. = 359, $p < .01$; root mean square residual [RMR] = .06; goodness-of-fit index [GFI] = .844; NFI = .899; comparative fit index [CFI] = .920; and root mean square error of approximation [RMSEA] = .07). However, the standardized factor loadings on three of the commitment items were below .50 (C9 = .419, C10 = .040, and C12 = .231). Therefore, we removed these items (for the revised nine-item commitment scale, $\alpha = .92$). The revised model provided a significantly improved fit to the data ($\chi^2 = 1095.34$, d.f. = 282, $p < .01$; RMR = .05; GFI = .871; NFI = .924; CFI = .942; and RMSEA = .07). Composite reliabilities were .95 for organizational trust, .93 for organizational commitment, .82 for job satisfaction, and .93 for intention to turnover. As such, all composite reliability coefficients were greater than .60, meeting Bagozzi and Yi's (1988) guideline for acceptability. We determined the measures' discriminant validity by examining the cross-variable correlations. We constructed 95% confidence intervals for each correlation coefficient. The intercorrelations were significantly ($p < .05$) less than one, providing support for the measures' discriminant validity.

We conceptualized job outcomes to have a more complex factor structure. Specifically, we believed that the components of job outcomes (i.e., organizational commitment, organizational trust, job satisfaction, and intention to turnover) represented a higher-order factor. This corresponds to a second-order confirmatory factor model, in which observed items are hypothesized to originate from the four first-order factors, and the first-order factors, in turn, originate from a second-order factor (see Table 3). The model satisfactorily fit the data ($\chi^2 = 1151.5$, d.f. = 287, $p <$

TABLE 3
Standardized Estimates for Job Outcomes as a Second-Order Factor

A: First-Order Loadings

Indicator	Commitment	Trust	Satisfaction	Intention to Turnover
C1	.679[a]			
C2	.731 (16.82)[b]			
C3	.879 (19.75)			
C4	.825 (18.67)			
C5	.729 (16.76)			
C6	.821 (18.64)			
C7	.820 (18.59)			
C8	.797 (18.16)			
C11	.572 (13.41)			
T1		.668[a]		
T2		.516 (12.28)		
T3		.742 (17.08)		
T4		.817 (18.55)		
T5		.874 (19.65)		
T6		.857 (19.35)		
T7		.876 (19.70)		
T8		.888 (19.94)		
T9		.845 (19.07)		
T10		.880 (19.78)		
S1			.768[a]	
S2			.556 (13.65)	
S3			.845 (21.49)	
S4			.725 (18.25)	
I1				.947[a]
I2				.880 (31.13)
I3				.878 (35.47)

B: Second-Order Loadings

Satisfaction	.909[a]
Commitment	.835 (16.34)
Trust	.924 (19.40)
Intention to turnover	.760 (19.05)

[a] Fixed parameters.
[b] t-values are in parentheses.

.00; RMR = .05; GFI = .860; NFI = .920; CFI = .939; and RMSEA = .07).

Results

H_1 argued that marketers perceive the governance structure as enabling them to obtain greater market-based value on less easily transferable capital (i.e., informational and organizational) than on more easily transferable capital (i.e., human and relational). On the basis of a paired sample t-test, the results support H_1 ($\bar{X}_{\text{more easily transferable capital}} = -.123$, $\bar{X}_{\text{less easily transferable capital}} = .675$; $t = -19.656$, $p < .001$).

We tested H_2 and H_3 with a structural equation model using AMOS 5.0 in SPSS and generalized least squares estimates (see Table 4; for common method variance testing, see Appendix E). We measured perceived governance structure related to both more and less easily transferable capital with two-item indexes respective of capital elements (i.e., relational and human for more easily transferable capital and information and organizational for less easily transferable capital). We used an averaged measure of each component of job outcomes (i.e., organizational commitment, organizational trust, job satisfaction, and intention to turnover) as an indicator for job outcomes. We measured perceived quantity of both more and less easily transferable capital with two-item indexes of their respective capital elements. The results indicate that the data fit the model acceptably ($\chi^2 = 150.745$, d.f. = 46, $p < .00$; GFI = .960; adjusted goodness-of-fit index [AGFI] = .932; incremental fit index [IFI] = .873; CFI = .870; NFI = .827; RMSEA = .060; and standardized root mean square residual [SRMR] = .054).

H_2 argued that the association of perceived governance structure for protecting marketers' capital investments with positive job outcomes would be stronger for more easily transferable capital than for less easily transferable capital. The results indicate that marketers' perceptions of the protective governance structure related to more easily transferable capital were positively associated with positive job outcomes ($\beta = .530$, $t = 6.106$, $p < .01$), whereas marketers' perceptions of the protective governance structure related to less easily transferable capital were not associated with positive job outcomes ($\beta = -.130$, $t = -1.638$, $p > .05$). We compared the standardized beta coefficients using AMOS 5.0, applying appropriate constraints and testing for signifi-

TABLE 4
Estimation Results

	Model (H_2 and H_3)		Mediation (H_4)	
	β (SE)	t-Value	β (SE)	t-Value
Perceived governance structure for protecting capital related to more easily transferable capital → job outcomes	.530* (.112)	6.106	.531* (.113)	6.147
Perceived governance structure for protecting capital related to less easily transferable capital → job outcomes	–.130 (.082)	–1.638	–.134 (.083)	–1.678
Job outcomes → accumulated more easily transferable capital	.155* (.038)	2.761	.233* (.047)	4.886
Job outcomes → accumulated less easily transferable capital	.258* (.036)	5.274	.280* (.042)	3.511
Perceived governance structure for protecting capital related to more easily transferable capital → accumulated more easily transferable capital			–.168 (.102)	–1.509
Perceived governance structure for protecting capital related to more easily transferable capital → accumulated less easily transferable capital			–.045 (.092)	–.472
Perceived governance structure for protecting capital related to less easily transferable capital → accumulated more easily transferable capital			.007 (.073)	.068
Perceived governance structure for protecting capital related to less easily transferable capital → accumulated less easily transferable capital			.002 (.065)	.024
χ^2		150.745		144.710
d.f.		46		42
Probability		.000		.000
GFI		.960		.962
AGFI		.932		.929
IFI		.873		.876
CFI		.870		.872
NFI		.827		.834
RMSEA		.060		.062
SRMR		.054		.051

*$p < .01$ (two-tailed t-test).

Notes: Model: number of observations = 631, and total number of parameters estimates = 32. Mediation: number of observations = 631, and total number of parameter estimates = 36.

cance. The standardized beta weights were significantly different at the $p < .05$ level (χ^2 difference = 20.05, d.f. = 1, $p < .001$), in support of H_2.

H_3 argued that marketers' positive job outcomes would be more positively related to the accumulation of less easily transferable capital than to the accumulation of more easily transferable capital. The results indicate that marketers' positive job outcomes were positively associated with their accumulation of less easily transferable capital ($\beta = .258$, $t = 5.274$, $p < .01$). The results indicate that marketers' positive job outcomes were also positively associated with their accumulation of more easily transferable capital ($\beta = .155$, $t = 2.761$, $p < .01$). We compared the standardized beta coefficients using AMOS 5.0, applying appropriate constraints and testing for significance. The standardized beta weights were significantly different at the $p < .05$ level (χ^2 difference = 5.419, d.f. = 1, $p < .025$), in support of H_3.

H_4 theorized that job outcomes mediated marketers' perceptions of the governance structure related to their capital and their accumulation of capital. We tested H_4 with the addition of four direct paths from marketers' perceptions of the governance structure related to their more and less easily transferable capital to their accumulation of more and less easily transferable capital to the structural equations model used to test H_2 and H_3. The data fit the model acceptably ($\chi^2 = 144.710$, d.f. = 42, $p < .00$; GFI = .962; AGFI = .929; IFI = .876; CFI = .872; NFI = .834; RMSEA = .062; and SRMR = .051), though the new model does not provide a significant improvement over the more parsimonious model we used to test H_2 and H_3 (χ^2 difference = 6.035, d.f. = 4, $p > .10$). The results support H_4, indicating that job outcomes fully mediate the relationship between marketers' perceived governance structure related to their capital and their capital accumulation. Specifically, the paths linking marketers' perceived governance structure on their more easily transferable capital and their accumulation of more and less easily transferable capital were not significant ($\beta = -.168$, $t = -1.509$, $p > .05$; $\beta = -.045$, $t = -.472$, $p > .05$, respectively). Furthermore, the paths linking marketers' perceived governance structure on their less easily transferable capital and their accumulation of more and less easily transferable capital were not significant ($\beta = .007$, $t = .068$, $p > .05$; $\beta = .002$, $t = .024$, $p > .05$, respectively).[6]

Discussion

This study was motivated by a desire to understand both the theoretical nature of the accumulation of capital elements (specifically capital that is less easily transferable) embodied by marketing personnel and how such knowledge could help advance the practice of marketing by providing insights into how to safeguard firm-specific capital that is embodied in marketers and is a key source of competitive advantage. As such, we proposed three questions: (1) How do marketing personnel perceive the governance structure in relation to the different types of capital that they embody? (2) What job outcomes accrue under governance structures related to marketers' capital? (3) How do job outcomes influence the accumulation of less easily transferable capital by a firm's marketing personnel? Our findings offer initial insights into these issues and provide significant implications for marketing academics and practitioners.

Theoretical Implications

The findings indicate that marketers' perceptions of governance differed on the basis of the capital's transferability. Specifically, our findings indicate that marketing personnel believed that they were able to obtain value in excess of market value on their less easily transferable capital and slightly less than market value on their more easily transferable capital. This finding provides empirical support to Williamson, Wachter, and Harris's (1975) and Ganesan and Weitz's (1996) theoretical arguments in that it supports the position that firms may view less easily transferable capital as important to the firm and therefore provide a market premium on this type of capital when it is embodied by marketing personnel. However, Williamson, Wachter, and Harris and Ganesan and Weitz argue that the premium is offered in an attempt to retain employees with specialized capital. As such, to examine the full theoretical argument, the relationship between perceived governance structure and job outcomes must be examined.

In exploring this relationship, we found that marketers' perceptions of the governance structure for less easily transferable capital were not related to job outcomes (i.e., organizational commitment, organizational trust, job satisfaction, and intention to turnover), whereas their perceptions of the governance structure related to more easily transferable capital were positively related to job outcomes. Although this result may seem counterintuitive, theoretically it can be argued that marketers' perceptions of the governance structure related to less easily transferable capital are mitigated by the initial and continuing cost of accumulating such capital. The costs of investing in less easily transferable capital include the creation of a power asymmetry in the employer–employee relationship, making marketers a potential hostage of the firm and, thus, more vulnerable to opportunistic behavior. This is an unexpected and important finding of our study because it moves the understanding of the employer–employee governance relationship beyond the simplistic "more-is-better" approach to rewarding marketer capital (i.e., simply rewarding marketers for their capital will result in positive job outcomes). Furthermore, the findings have significant implications for senior marketing managers in terms of retention of marketers (and the theoretical argument that simply valuing less easily transferable capital will aid in retention) because they demonstrate that even when marketing personnel perceive a protective governance structure as existing in relation to less easily transferable capital (as found in H_1), it does not have the same job outcome payoff as more easily transferable capital (as found in H_2).

Our findings also provide substantially new insights into the accumulation of capital by marketing personnel. Prior research indicates that firm success is founded on capital that is both heterogeneous and imperfectly mobile. As such, firms must not only maintain their capital accumulation through stimulation of positive job outcomes that enhance internal coordination and retention of key marketing personnel but also stimulate capital accumulation of less easily transferable capital by their marketers. Our findings indicate that positive job outcomes stimulate marketers to accumulate a greater amount of less easily transferable capital than more easily transferable capital, thus providing the firm with the specialized capital theorized to establish and maintain a competitive advantage.

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[6] Furthermore, to minimize the spuriousness of the results, we tested two additional control variables (i.e., job dependency and job market uncertainty) on job outcomes in the fully mediated model. The results of the additional testing indicate that (1) neither variable significantly influenced job outcomes and (2) the control variable model had a significantly worse fit to the data.

More important, the finding that the relationship between marketers' perceptions of the governance structure related to their capital and marketers' capital accumulation is mediated by job outcomes substantially enhances the understanding of the influence of governance structure on job outcomes and capital accumulation. Specifically, the findings indicate that marketers do not invest in the accumulation of specific classifications of capital solely on the basis of how these elements of capital are valued (i.e., a lack of a direct relationship); rather, the stimulation of reciprocity through a governance structure characterized by dignity stimulates marketers to invest in the accumulation of less easily transferable capital. As such, the findings indicate that the protective governance structure implied by transaction cost economics does not fully explain the stimulation of the accumulation of less easily transferable capital. Consequently, this work extends that of Anderson and Robertson (1995) and Grossman and Hart (1986) and indicates that a marketer is willing to invest in the accumulation of specific capital when he or she is embedded in a relationship that stimulates positive job outcomes.

Managerial Implications

From a managerial standpoint, the study presents insights into three important areas for senior marketing managers who are charged with developing a governance mechanism to both retain current marketing talent and develop a more effective marketing team: (1) marketers' perceptions of the governance structure related to the capital they embody, (2) firm efforts and strategies to encourage marketers to accumulate capital, and (3) marketer retention strategies. First, we found that marketing personnel believe that firms allow them to obtain more than the market-based value of less easily transferable capital elements and overall slightly less than market-based value on more easily transferable elements. The findings suggest that senior marketing managers recognize that less easily transferable capital is important to the firm, and as such, the firm demonstrates its commitment to marketers through a protective governance structure that enables them to capture greater value on this classification of capital. However, marketers also invest in less easily transferable capital, which limits mobility and potentially creates hostage situations for marketers, indicating that simply providing a protective governance structure related to less easily transferable capital may lack effectiveness in stimulating the accumulation of less easily transferable capital and retaining marketers who have accumulated this type of capital. Thus, the question for senior marketing managers who are accountable for marketers under their command is, What stimulates marketing personnel to accumulate less easily transferable capital?

Second, when marketers join a firm, the employer often invests in training to assist them in accumulating less easily transferable capital (e.g., product-specific knowledge, understanding of up-selling techniques for customer relationship marketing). It could be argued that a firm undertakes this investment because it recognizes that its effectiveness increases as its marketing personnel increase their accumulation of less easily transferable capital. Thus, such training serves as a commitment on the part of the firm. In acknowledging the firm's commitment to them, marketers willingly accumulate less easily transferable capital (partly because they view it as their responsibility and partly to enhance their job opportunities within the firm). However, although marketers will begin to accumulate less easily transferable capital, they will continue to do so only if they believe that they are able to obtain value on more easily transferable capital. As such, the findings of this study indicate that a protective governance structure related to more easily transferable capital may be an effective strategy to enhance marketers' accumulation of less easily transferable capital. However, this relationship exists only through the stimulation of positive job outcomes and therefore has retention implications.

Third, retention of marketing personnel who have accumulated less easily transferable capital is necessary for the effective operation and performance of the marketing function within a firm. The findings of this study indicate that though rewarding marketers for their less easily transferable capital is important (when marketers believe that they cannot obtain greater value on less easily transferable capital than they could externally, they may view the firm acting opportunistically, thus negatively influencing job outcomes), it is not necessarily the most effective way to stimulate positive job outcomes (which are necessary for the stimulation of marketers' accumulation of less easily transferable capital). Rather, the findings indicate that a protective governance structure related to marketers' more easily transferable capital elements is a more effective strategy for retention than rewarding them for their accumulated less easily transferable capital. For example, consider marketers who earn an MBA degree while working full time. On completion of their MBA degree, how do their firms reward them? Often, the firm does not reward them for their degree. This is particularly notable when a firm does not maintain a continuing education policy. As such, marketers may view the firm as not valuing them for the obtainment of an MBA (i.e., acting opportunistically or not providing the perceived dignity it should, given marketers' additional capital they provide to the firm through the advanced degree). From the firm's standpoint, the MBA degree, which is an easily transferable capital element, may provide little competitive advantage. When marketing personnel do not believe that they are able to obtain value for the obtainment of the degree, their job outcomes diminish (e.g., decreased organizational trust, increased intention to turnover).

However, the findings do not imply that senior marketing managers who are responsible for marketing personnel should employ a protective governance structure in relation to all their marketers who accumulate more easily transferable capital. Rather, the findings suggest that they should engage in a protective governance structure only with marketers who have less easily transferable capital that the firm wants to safeguard. Each marketer embodies each of the four elements of capital, albeit in differing quantities. Therefore, firm valuation of each element of capital has repercussions on the marketer as a whole. If the marketer leaves the employment of the firm, the employer does not lose only a portion of the marketer's capital; it loses *all* the capital embodied by the marketer, thus diminishing the effectiveness of its marketing function. Thus, it becomes important for senior marketing managers to monitor the market value of a marketer's capital carefully and adjust the governance structure employed within their firm accordingly.

Limitations and Further Research

This study has several limitations, which we address in combination with suggestions for future research directions. The central issue of this study is how marketers' perceptions of the governance structure used to protect their capital influence job outcomes and, ultimately, their capital accumulation. To explore this issue, we framed our measures as marketers' attitudes and behaviors (i.e., job outcomes and capital accumulation) derived from their perceptions of the governance structure (i.e., perceived ability to obtain value on their capital). Thus, similar to other research in marketing on job outcomes, our construct operationalizations were founded at the individual marketer level. This provides several nuances that are required for interpretation. The measures come from the same source, which leads to the same concerns as in prior self-report studies, namely, the issue not only of common method variance but also of whether marketers can provide accurate evaluations of their capital and its valuation. Although Harman's one-factor test, a partial correlation test, and a fully mediated model suggest that common method bias does not influence our results, the collection of all data from a single source poses the potential of biasing the results. Further research could employ multiple data sources to overcome this issue. Furthermore, consistent with prior research in marketing on job outcomes, we argue that marketers respond to their perceptions of reality, and thus their job outcomes are influenced by their perceptions of the governance structure related to their capital, regardless of the accuracy of their perceptions. For example, if marketers believe that they are not able to obtain market-based value for their capital from their current firm, even if their capital is accurately valued by the firm, negative job outcomes will result because they will behave on the basis of their perceptions of how they are valued. Further research could build on the measures we presented here through the incorporation of secondary measures that provide insights into the accuracy of marketers' perceptions of their capital and its value. For example, further research could collect not only marketers' perceptions of their accumulated capital and its value but also the perceptions of their senior marketing managers. Through a comparison of matched data, a greater understanding of both parties to the governance relationship could be gained, thus leading senior marketing managers to govern marketing personnel more effectively.

An additional limitation of this study is derived from its cross-sectional design. Although the results of this study strongly suggest, and theoretically support, the notion that marketers' perceptions of the governance structure related to their capital are a stimulating mechanism for positive job outcomes and resultant capital accumulation, inferences to causality are limited given the cross-sectional nature of the data set. Thus, the retention and capital accumulation benefits of employee governance should be examined longitudinally. Furthermore, under a longitudinal perspective, additional topics could be integrated to enhance the understanding of this topic. For example, in investigating supply chain relationships, Jap and Ganesan (2000) theorize that bilateral investments are more effective in stimulating a strong relationship in the exploration phase of the relationship than during the buildup, maturity, or decline phases. Thus, further research could explore how time, or stage of the employer–employee relationship, moderates the influence of investment decisions on the part of the firm and marketing personnel in relation to job outcomes. For example, it could be argued that during the initial employment phase, marketers perceive the firm's investment in their training as a commitment to them, whereas in subsequent stages, marketers may view these investments as attempts by the firm to create a hostage situation. As such, different influences on job outcomes would result. Given the importance of establishing effective governance mechanisms for marketing personnel at all stages of the employment life cycle, research addressing this topic could substantially contribute to the advancement of knowledge in this area.

The issues of job outcomes and capital accumulation are important topics to senior marketing managers who are accountable for a firm's marketing performance and the marketers under their command. In this study, we find that marketers' perceptions of the governance structure related to the capital they embody influence job outcomes and, ultimately, marketer capital accumulation. These findings shed light on the issues that are central to firms retaining key marketing personnel and the senior marketing manager strategies to encourage marketers to invest in the accumulation of capital. Thus, this study both contributes to the literature and provides a foundation for future work with respect to employer–employee governance, job outcomes, capital accumulation, and the importance of marketers (and their capital) in the firm. Specifically, it could be argued that our conceptualization and operationalization of capital could be extended to other functional areas, such as finance, production, information systems, and accounting. Given the increased questioning of marketing's role in the firm (Webster 1992; Webster, Malter, and Ganesan 2005), it could be valuable to the marketing profession to understand the marketer's role as being a carrier and transmitter of capital. If marketing personnel and other firm personnel can embody elements of capital and if these elements of capital are a major source of firm advantage, the relative value of marketing personnel and other functional area personnel to the firm can become more clearly evident. Further research that examines the relative influence of capital that different groups of firm employees embody on competitive advantage would provide substantial insights into the marketing discipline.

Appendix A
Measurement Scales: Internal Value

Please respond to the following statements regarding the value you believe *your employer* places on each of the following:

Human

- The business skills I have acquired are valuable to my employer. (IVH1)
- My business capabilities are valuable to my employer. (IVH2)
- My business education and training are valuable to my employer. (IVH3)
- My business expertise is valuable to my employer. (IVH4)

Relational

- My network of business contacts is valuable to my employer. (IVR1)
- My business connections are valuable to my employer. (IVR2)
- The business relationships that I have developed are valuable to my employer. (IVR3)
- My business acquaintances are valuable to my employer. (IVR4)

Organizational

- My knowledge of the way my employer does things is valuable to them. (IVO1)
- The knowledge I have about the policies of my employer is valuable to them. (IVO2)
- The knowledge I have about the practices and procedures of my employer is valuable to them. (IVO3)
- My knowledge about the way my employer operates is valuable to them. (IVO4)

Informational

- My knowledge about my employer's products/services is valuable to them. (IVI1)
- My knowledge about my employer's competitors is valuable to them. (IVI2)
- The knowledge I have about my employer's customers and clients is valuable to them. (IVI3)
- My knowledge of the industry is valuable to my employer. (IVI4)

Appendix B
Measurement Scales: External Value

Please respond to the following statements regarding the value you believe *other employers* (i.e., employers that you could potentially work for) would place on each of the following:

Human

- The business skills I have acquired are valuable to other employers. (EVH1)
- My business capabilities are valuable to other employers. (EVH2)
- My business education and training are valuable to other employers. (EVH3)
- My business expertise is valuable to other employers. (EVH4)

Relational

- My network of business contacts is valuable to other employers. (EVR1)
- My business connections are valuable to other employers. (EVR2)
- The business relationships that I have developed are valuable to other employers. (EVR3)
- My business acquaintances are valuable to other employers. (EVR4)

Organizational

- My knowledge of the way my employer does things is valuable to other employers. (EVO1)
- The knowledge I have about the policies of my employer is valuable to other employers. (EVO2)
- The knowledge I have about the practices and procedures of my employer is valuable to other employers. (EVO3)
- My knowledge about the way my employer operates is valuable to other employers. (EVO4)

Informational

- My knowledge about my employer's products/services is valuable to other employers. (EVI1)
- My knowledge about my employer's competitors is valuable to other employers. (EVI2)
- The knowledge I have about my employer's customers and clients is valuable to other employers. (EVI3)
- My knowledge of the industry is valuable to other employers. (EVI4)

Appendix C
Measurement Scales: Quantity of Capital

Each of us has a different degree of knowledge and/or skills. For each of the following statements, please indicate your agreement or disagreement with a score from 1 to 7.

Human

- I have many business skills. (QCH1)
- I have many business capabilities. (QCH2)
- I have a great deal of business education and training. (QCH3)
- I have a great deal of business expertise. (QCH4)

Relational

- I have a large network of business contacts. (QCR1)
- I have many business connections. (QCR2)
- I have developed many business relationships. (QCR3)
- I have developed many business acquaintances. (QCR4)

Organizational

- I know a great deal about the way my employer does things. (QCO1)

- I have a great understanding of my employer's policies. (QCO2)
- I know a great deal about the practices and procedures of my employer. (QCO3)
- I have a great understanding about the way my employer operates. (QCO4)

Informational

- I know a great deal about my employers products/services. (QCI1)
- I have a great understanding about my employer's competitors. (QCI2)
- I know a great deal about my employer's customers and clients. (QCI3)
- I have a great knowledge of the industry. (QCI4)

Appendix D
Measurement Scales: Job Outcomes

Organizational Commitment (1 = "strongly agree," and 7 = "strongly disagree")

- Since joining this employer, my personal values and those of the organization have become more similar. (C1) (reverse coded)
- If the values of my employer were different, I would not be as attached to this firm. (C2) (reverse coded)
- The reason I prefer this organization to others is because of what it stands for, its values. (C3) (reverse coded)
- My attachment to this employer is primarily based on the similarity of my values and those represented by the organization. (C4) (reverse coded)
- What this organization stands for is important to me. (C5) (reverse coded)
- I am proud to tell others that I am a part of this firm. (C6) (reverse coded)
- I talk up my employer to my friends as a great organization to work for. (C7) (reverse coded)
- I feel a sense of "ownership" for this organization rather than being just an employee. (C8) (reverse coded)
- Unless I'm rewarded for it in some way, I see no reason to expend extra effort on behalf of this organization. (C9)
- How hard I work for my employer is directly linked to how much I am rewarded. (C10)
- My private views about my employer are different than those I express publicly. (C11)
- In order for me to get rewarded around here, it is necessary to express the right attitude. (C12)

Organizational Trust (1 = "strongly agree," and 7 = "strongly disagree")

- Even when my employer gives me a rather unlikely explanation I am confident that it is the truth. (T1) (reverse coded)
- My employer has often provided me with information that has later proven to be inaccurate. (T2)
- My employer usually keeps the promises that it makes to me (T3) (reverse coded)
- Whenever my employer gives me advice, I know that it is sharing its best judgment. (T4) (reverse coded)
- I can count on my employer to be sincere. (T5) (reverse coded)
- Though circumstances change, I believe that my employer will be ready and willing to offer me assistance and support. (T6) (reverse coded)
- When making important decisions, my employer is concerned about my welfare. (T7) (reverse coded)
- When I share my problems with my employer, I know that it will respond with understanding. (T8) (reverse coded)
- In the future, I can count on my employer to consider how its decisions and actions will affect me. (T9) (reverse coded)
- When it comes to things that are important to me, I can depend on my employer's support. (T10) (reverse coded)

Job Satisfaction (1 = "very satisfied," and 7 = "very dissatisfied")

- Your job. (S1) (reverse coded)
- Your pay/benefits. (S2) (reverse coded)
- The recognition you receive for a job well done. (S3) (reverse coded)
- The amount of say you have in how the work is to be done. (S4) (reverse coded)

Intention to Turnover (1 = "strongly agree," and 7 = "strongly disagree")

- I am planning to leave my job for another in the near future. (I1)
- I am thinking of quitting this job and finding another. (I2)
- I would like to quit this job and find another in the near future. (I3)

Appendix E
Common Method Variance Testing

We employed several techniques to examine the potential for common method variance. First, following the work of Olson, Slater, and Hult (2005), we used the CFA approach to Harman's one-factor test. This test assesses the threat of common method bias by indicating whether a single latent factor would pose an alternative explanation to the analysis (Podsakoff et al. 2003). The one-factor latent model yielded a chi-square of 782.72 (d.f. = 53; for the measurement model, χ^2 = 300.77, d.f. = 43). The fit of the one-factor model was significantly worse than that of the measurement model, suggesting that common method variance is not a serious problem. Second, considering possible limitations of Harman's one-factor test, we employed the partial correlation procedure of including a marker variable within the model. Lindell and Whitney (2001) argue that common method variance can be assessed by identifying a marker variable (i.e., a variable that is not theoretically related to at least one other variable in the study). For the purposes of testing, we used respondent age as the marker variable. The marker variable was not significantly related to any of the variables in the model, thus suggesting that common method variance is not a serious problem. Furthermore, our model demonstrates full mediation, which argues against common method variance significantly influencing the results.

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Sandy D. Jap

The Impact of Online Reverse Auction Design on Buyer–Supplier Relationships

As the use of online reverse auctions in industrial-sourcing activities grows, buyers and suppliers are increasingly concerned about these auctions' effects on their interorganizational performance (i.e., suspicions of opportunism, overall satisfaction, and future expectations). This research examines how the buyer's auction design (i.e., the number of bidders, the economic stakes, and price visibility) and the price dynamics over the course of the auction affect its relationship with suppliers. Analysis of 25 quasi experiments involving 125 suppliers and $385 million in procurement contracts suggests that the larger the number of bidders, the larger the economic stakes, and the less visible the price in an auction, the more positive is the impact on the interorganizational relationship. Large price drops (higher savings) over the course of the event have a detrimental effect on the buyer–supplier relationship. For auctions in which the lowest bidder wins, there is a decrease in opportunism suspicions as the economic stakes of the auction increase, and there is an increase in opportunism suspicions in auctions with greater price visibility. Implications for the management of industrial procurement activities are considered.

> Designing the right kind of auction will have as big an impact on the brand, customer loyalty, and profit margins of the undertaking as will the designing of the right kind of products.
>
> —Economist Hal Varian (Schrage 2000)

The use of online reverse auctions is becoming a permanent fixture in industrial sourcing, and they have been used to procure billions in parts and services in the government sector and virtually every major industry.[1] Although the current usage of these auctions as applied to a firm's overall spending is still in the single-digit range, the potential applicability of these auctions is as high as half of the firm's annual expenditures, with 10%–15% on average being most likely (Beall et al. 2003). Thus, there is substantial opportunity for growth, and these auctions already have had, and will continue to have, a profound impact on the process and manner in which firms source their goods and services.

There has also been a corresponding growth in interest among academic researchers, who have considered these auctions from a variety of perspectives, such as computer science, economics, marketing, operations research, and sociology. In 2003, *Management Science* featured a two-part special issue on e-business, in which online auctions and e-procurement represented the largest proportion (32%) of all the articles featured. Despite this growing attention, there is little work that considers the interface between online reverse auctions and the interorganizational context in which these auctions are deployed, even though the burgeoning literature on interorganizational relationships indicates that the buyer–supplier relationship plays a critical role in determining performance outcomes for both parties and can serve as a key source of strategic advantage.

The online reverse auction experience can affect the buyer's interorganizational relationship with the supplier in two ways: through the supplier's experience over the course of the auction and through the auction outcome itself (i.e., whether the supplier won the contract bid). However, the latter is less interesting than the former because it is expected that winning the auction would be better for the buyer–supplier relationship than losing. Moreover, the buyer cannot determine the auction outcome *ex ante*. However, the supplier's experience in the auction is, in large part, a function of the buyer's *ex ante* choices regarding the auction design, such as the number and type of participants, the contract size, and the format (i.e., the degree of price visibility and award rule). Because online reverse auctions are initiated and directed by buyers toward their suppliers, I consider how the buyer's choices of design elements affect the supplier's view of its relationship with that buyer; specifically, I consider the supplier's evaluations (i.e., satisfaction and opportunism suspicions) and future expectations (i.e., continuity intentions).

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[1] The term "reverse" reflects the fact that sellers rather than buyers bid and that the goal of the auction is to drive price down rather than up.

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In their research on the benefits and risks of online reverse auctions, Smeltzer and Carr (2003) find that the loss of trust and impact on the buyer–supplier relationship is an overwhelming cause for concern for both buyers and suppliers. Only 5% of the people they interviewed suggested that online reverse auctions could potentially improve relationships. This implies that as much as 95% of the participants in online reverse auctions might not view them as helpful to relationships. Consistent with this conjecture, Carter and colleagues (2004) find that the vast majority of suppliers they interviewed reported that their relationship with the buyer was adversely affected. Jap (2003) provides quantitative evidence that the use of open bid (full price visibility) online reverse auctions adversely affects buyer–supplier relationships by raising supplier suspicions of buyer opportunism.

In light of this, it is imperative that buyers understand how to design online auctions in such a way as to minimize potentially adverse effects on their supply relationships and evaluate the impact of their decisions from the suppliers' perspective. This research is an initial step in this direction. I draw on relevant theory in the interorganizational relationship management literature and emerging work on online reverse auctions as well as extensive field interviews with industrial buyers, suppliers, and online auctioneers to develop a set of refutable predictions about how the design and structure of online reverse auctions might shape the interorganizational buyer–seller relationship.

The connection between auction design and interorganizational relationship outcomes is empirically examined through the use of a quasi-experimental design, in which proprietary, primary data on relationships with buying organizations are collected from 125 suppliers before and after 25 online reverse auctions in various product categories and firms. The data are unique and enormously difficult to obtain, but despite their limitations, they provide intriguing insights into and unique learning opportunities for the relational impact of the design and structure of online reverse auctions on interorganizational outcomes. I also collect data on the design characteristics of each auction and model the extent to which they exert a systematic impact on the supplier's behaviors, evaluations, and expectations of its relationship with the buyer. I do not explicitly test the explanatory mechanisms but rather consider the degree to which the data are consistent with ("as-if") my reasoning.

In what follows, predictions are developed that relate the design elements of online reverse auctions to supplier behavior, evaluations, and expectations. The quasi-experimental methodology is described along with an empirical examination of the data. The article concludes with a discussion of the results, directions for further research, and implications for management.

Conceptual Framework

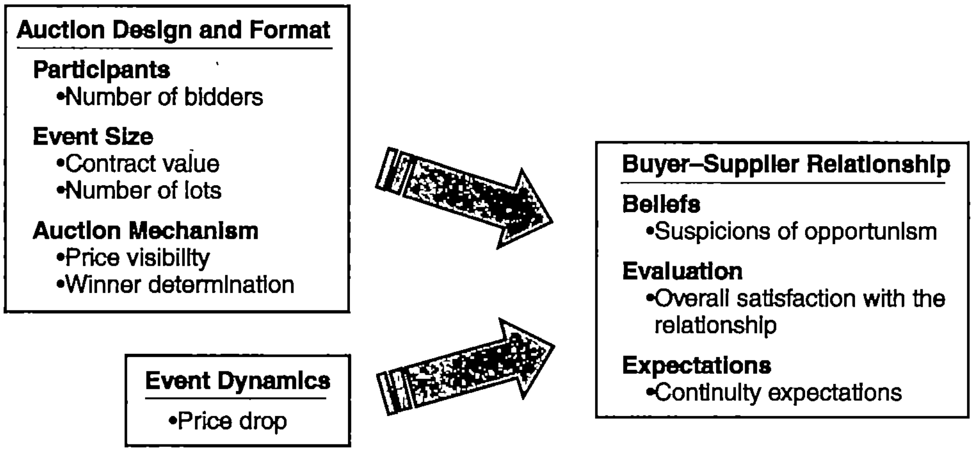
Throughout the discussion and methodology, the unit of analysis is the perspective of an individual supplier (not an online event) that is participating in an online reverse auction with one specific buyer. The auction design characteristics vary systematically across the auctions.

An overview of the conceptual model is provided in Figure 1. The general intuition is that the supplier's relationship with the buyer is affected by two attributes of the online reverse auction event: (1) the design and format of the auction and (2) the price dynamics in the auction. The former is controllable by the buyer, and the latter is not. I begin with a brief review of the literature that is relevant to online reverse auctions and definitions of the supplier's beliefs, evaluations, and expectations in the interorganizational relationship. Then, the specific auction design aspects and event dynamics are described, and predictions relating these to the interorganizational relationship are developed.

Online Reverse Auctions

Research that considers how auctions affect, or are affected by, the organizational contexts or the participants is emerging. Although sociologists have not developed a large literature on auctions, they have examined repeated auctions involving the same people, finding that people involved in repeated auctions tend to behave in ways consistent with

FIGURE 1
Conceptual Framework



social behavior theories rather than economic theories. Smith (1990) develops this view in more detail.

With regard to online reverse auctions, there are numerous studies that describe the online reverse auction process from preliminary steps to contract awards (see, e.g., Emiliani 2000; Mabert and Skeels 2002; Stein, Hawking, and Wyld 2003). Jap (2002) provides a conceptual overview of the differences between online reverse auctions in the marketplace and both physical auctions and those of the theoretical literature, as well as the conditions, structure, and evaluation of online reverse auctions. Kaufmann and Carter (2004) consider the conditions under which products should be auctioned electronically or in face-to-face negotiations.

Several studies have considered who the winners and losers are of online reverse auctions. For example, Smeltzer and Carr (2003) conduct 41 depth interviews to identify the potential benefits and risks of online reverse auctions for buyers and suppliers. Mabert and Skeels (2002) and Stein, Hawking, and Wyld (2003) rely on an in-depth case study to accomplish this. Haruvy, Rao, and Unver (2005) examine the conditions under which the buyer or supplier benefits from online reverse auctions from an analytical perspective, finding that differentiated suppliers in price-based auctions are economically worse off than buyers and that this relationship reverses when auctions that incorporate nonprice features are used.

There are several studies related to the intersection of online reverse auction design and its impact on interorganizational relationships (see, e.g., Carter et al. 2004; Jap 2003; Millet et al. 2004). Subsequently, I review these studies and outline the important ways the current research coincides and differs from them.

Millet and colleagues (2004) examine how various levels of supplier participation (i.e., invitation, logging into an event, and bidding) and auction characteristics (i.e., auction format and price visibility) affect the total price savings that an online auction event generates. They use data from more than 14,000 auctions and find that different auction formats lead to different levels of supplier participation and savings.

Carter and colleagues (2004) examine similar issues, but they rely on depth interviews with buyers, suppliers, and auctioneer participants in online reverse auctions. They attempt to deduce the impact of auctions on productivity and cycle time and consider the design factors associated with auction success, which they define as the perceived price savings from the online auction compared with face-to-face negotiations. They find that more successful auction events also tend to have a higher number of bidders, larger purchasing contracts, and lots and use a partial price visibility format. Although both Carter and colleagues and Millet and colleagues consider auction characteristics similar to those considered in the current research, both authors specifically focus on the drivers of price reductions, not on the buyer–supplier relationship per se.

Both studies underscore the notion of auction design as an important strategic variable in determining auction revenues or savings. Although the independent variables that constitute auction design are not theoretically derived, they are a function of the specific online market context, and because both studies focus on the economic outcomes, they can evaluate these variables across thousands of auctions. The current research examines design predictor variables similar to those in Millet and colleagues' (2004) study, but my perspective differs in important ways. The final bid prices generated in online auctions are important and can affect buyer–supplier relationships directly, but they fail to capture key aspects of interorganizational performance, such as quality, reliability, long-term supplier viability (Forker, Ruch, and Hershauer 1999; Narasimhan, Talluri, and Mendez 2001), and market conditions. Economic outcomes also fail to account for beliefs, evaluations, and expectations that are the critical building blocks of the buyer–supplier relationship. Thus, the dependent variables in this research (opportunism suspicions, overall satisfaction, and continuity expectations) are completely different and broader in scope than those used in prior research. Moreover, data on the specific nature of buyer–supplier relationships are significantly more difficult to obtain, requiring a customized, dynamic intervention around online reverse auction events, and as such, the sample size is considerably smaller than those in other studies on auction design.

To date, Jap's (2003) study is the only research that explicitly considers the impact of online reverse auctions on buyer–supplier relationships, finding that full price visibility auctions increase the supplier's suspicions that the buyer is acting opportunistically, whereas sealed-bid (no price visibility) auctions are less threatening and serve as an important wake-up call, increasing the supplier's willingness to make dedicated investments in the buyer. Although the current research and Jap's (2003) are both focused on the impact of the auction process (as opposed to the auction outcome) on the interorganizational relationship and use a similar research design, there are several key differences. For example, Jap (2003) considers only the two extremes of full price visibility and no price visibility, whereas the current research considers a popular intermediate option: partial price visibility. Moreover, Jap (2003) examines auctions that have just been introduced to the supply base, whereas the current research examines auction practices that have been ongoing and involve experienced buyers and bidders. Jap (2003) uses only 6 auctions, all conducted by a single organization in one industry, whereas the current research uses 25 auctions conducted by four different buying organizations in a variety of industries (automotive, chemicals, consumer products, and high tech). Finally, Jap (2003) takes a limited view of the buyer–supplier relationship, considering only suspicions of opportunism and willingness to make customized investments, whereas the current research investigates a wider range of independent variables (i.e., partial price visibility formats, number of bidders, event size, and winner determination) and dependent variables (i.e., beliefs, outcomes, and expectations of suppliers).[2] By considering a wider range of variables and contexts as well as many more design elements, the current research expands the understanding of the impact of online reverse auctions on buyer–supplier relationships and, more broadly, the interface between online technologies and critical interorganizational processes.

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[2] Thus, whereas Jap's (2003) work provides a useful starting point for understanding how online reverse auctions affect buyer–supplier relationships, it is relatively limited in terms of the number and types of specific design elements, product categories, outcome variables, and industries considered.

The Interorganizational Relationship

In this subsection, I consider three facets of the interorganizational relationship that broadly influence the supplier's suspicions and evaluations of its relationship with the buyer: (1) the supplier's suspicions of buyer opportunism, (2) its overall satisfaction with the relationship, and (3) its expectations of continuity with the buyer. All three aspects are widely examined in the extensive literature on interorganizational relationships and are often recognized as critical aspects of successful buyer–supplier relationships. Opportunism suspicions provide insight into the supplier's fundamental assumptions about the buyer's behavior and motives in the relationship. Overall satisfaction with the relationship is a key performance outcome, and expectations of continuity point to future exchange intentions.

Opportunism suspicions. A central tenet of exchange is that economic actors act opportunistically; that is, they seek their self-interests with guile. Opportunism has received increasing attention in recent years (see Brown, Dev, and Lee 2000; Jap and Anderson 2003; Wathne and Heide 2000) and is synonymous with misrepresentation, cheating, and deception, subsuming a range of (mis)behaviors, such as adverse selection, moral hazard, shirking, subgoal pursuit, agency costs, and free riding (Williamson 1996). Unlike distrust, which is a broad, metaconstruct with many facets and levels, opportunism is more delimited and behavioral in nature and should create reduced attributions of trust.[3] I focus on the supplier's suspicions of opportunism rather than proven opportunism because the supplier typically cannot verify that the buyer is acting with guile.

Overall satisfaction with the relationship. The supplier's overall satisfaction with the relationship is a positive affective state that results from the appraisal of all aspects of a working relationship; it is a noneconomic measure in that it reflects the supplier's current overall attitude toward its relationship with a buyer (see Ruekert and Churchill 1984). This appraisal is conditioned on the supplier's expectations such that confirmation or exceeding these expectations leads to varying levels of satisfaction, whereas disconfirmation of the expectations reduces satisfaction or creates dissatisfaction. This conceptualization of satisfaction is one of the most studied outcome variables in interorganizational management research (for a review, see Gaski 1984; Geyskens, Steenkamp, and Kumar 1999; see also Ruekert and Churchill 1984).

Expectations of continuity. The supplier's expectations of relationship continuity reflect its perspective on the long-term viability of the relationship. When a firm expects that the relationship will continue into the future, it is more willing to engage in processes and make investments that will enhance the relationship in the long run (Anderson and Weitz 1989; Heide and Miner 1992). Confidence in the future of the relationship is important, because without it, the supplier may adopt a short time horizon and refuse to engage in activities that do not pay off quickly and with certainty (Williamson 1993). The supplier might also be more likely to adopt a zero-sum game approach to exchange or a "tit-for-tat" attitude (Axelrod 1984) that could be dysfunctional to the well-being of the relationship in the long run.

Auction Design Aspects and Predictions

In this subsection, I consider specific aspects of auction design and develop the arguments for predictions. Every buying organization faces a set of choices regarding the composition of an online reverse auction. Broadly speaking, these choices involve the participants, the size of the event, and the auction mechanism. Industrial reverse auctions are typically only open to a set of selected bidders, who may vary in terms of their capabilities, capacities, cost curves, quality levels, and history with the buyer. The event size speaks to whether the economic stakes of the auction are significant enough to motivate the supplier to participate and provide competitive pricing, and the auction mechanism defines the bidding procedure—that is, the degree to which elements of the bid are disclosed to the bidders, how the closing price is set, and how the winner is determined. Another important element of the online reverse auction event that may shape the buyer–supplier relationship is the event dynamics, which characterize the degree of price movement over the course of the event. I now describe these four facets. It is important to note that each could be examined in myriad ways; for example, many characteristics of the participants are arguably important in terms of determining the nature of the subsequent buyer–supplier relationship. However, it is beyond the scope of this research to consider all the possibilities. Instead, I provide an initial consideration in the hope that it will stimulate further research on other attributes of auction design.

Participants. The buyer invites a select group of bidders and often completes prequalification examinations to ensure that bidders are capable of fulfilling the purchase contract. A primary decision is the number of bidders that should be invited to participate in the auction. In general, increasing the number of bidders raises price competition and the savings generated by the auction (see Bulow and Klemperer 1996). Consistent with this, Millet and colleagues (2004) find that bidder participation in an online reverse auction significantly improves with the number of bidders; the average number of bids from five-plus suppliers in an online reverse auction is more than double the number of bids in auctions with fewer than five suppliers. Given the potential for increasing price competition and decreasing margins as the number of bidders increases, suppliers are unlikely to view auctions with a large number of bidders positively. In this case, suppliers' suspicions of buyer opportunism may increase, and their overall satisfaction with the relationship and desire to continue working with the buyer in the future may decrease as they view the buyer as aggressively trying to cut supply base margins. Thus:

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[3] Scholars across multiple disciplines do not fundamentally agree on the meaning of trust (Rousseau et al. 1998).

P_1: As the number of bidders in an online reverse auction event increases, there is a negative impact on the interorganizational relationship.

Event size. The size of the event speaks to the value of the purchase contract. I consider two indicators of the economic stakes of the auction: (1) the value of the purchase contract and (2) the number of lots in the event. In general, the expectation is that higher economic stakes and increased opportunity motivate suppliers to participate in the auction.

The value of the purchase contract typically refers to the historic spending level for the specific contract or the expected value of a new purchase contract. The larger the contract value, the greater is the motivation to participate in the online reverse auction event (Grewal, Comer, and Mehta 2001). Millet and colleagues (2004) find that supplier acceptance rates of invitations to participate in an online reverse auction increases with the total value of the auction and decreases for auctions with fewer than three items. As the contract value increases, it becomes more worthwhile to provide intangible value by being responsive to and supportive of the buyer. Moreover, higher stakes might also signal the buyer's commitment to make the exchange successful (see Anderson and Weitz 1992). In turn, this should reduce suspicions that the buyer is acting opportunistically and enhance the supplier's satisfaction and desire to continue working with the buyer in the future.

P_2: As the contract value in an online reverse auction event increases, there is a positive impact on the interorganizational relationship.

Another motivating factor is the number of product lots in the event. A product lot is a grouping of items that are typically organized according to the suppliers' capabilities to bid on or produce each lot, similarities in manufacturing processes, delivery regions, and so forth. For example, if a buyer needs to procure 20 rubber parts, the buyer may group the parts into five lots, in which each lot is composed of parts that use similar manufacturing processes, subparts, or supplier capabilities. Buyers award contracts on the basis of lots and do not accept bids for partial lots or individual parts within a lot. Thus, suppliers must be capable of producing all parts within a lot. Because suppliers are able to choose whether to bid on any given lot, the lots also indicate the match between supplier capabilities and buyer needs; that is, suppliers will not bid on product configuration lots that they are not capable of supplying, because their bids are legally binding. By grouping the parts into lots, the supplier needs to produce only 5 (as opposed to 20) bids and can leverage economies of scale and manufacturing processes across products.[4] As the number of lots in an event increases, it creates more varied opportunities in which the supplier can participate in bidding on the contract (Carter et al. 2004). Moreover, by combining lots into a consolidated spend, the total economic stakes are raised for the supplier, which may be the motivation necessary to gain the supplier's participation in the event.

A potential counterargument is that the number of lots can be demotivating because too many lots may make the bidding process more complex. Because suppliers typically bid sequentially on the lots in an event, each subsequent bid on a lot may be conditioned on a previous bid because the supplier typically attempts to allocate a fixed capacity and resources across multiple selling opportunities. Thus, it is possible that in extreme cases, a large number of lots could be discouraging to the supplier's bidding efforts. On average, I anticipate that as the number of lots increases, the buyer provides more ways for a greater range of suppliers to participate and more varied opportunities to win a part of the total contract.

P_3: As the number of lots in an online reverse auction event increases, there is a positive impact on the interorganizational relationship.

Auction mechanism. The auction mechanism describes the bidding process—that is, the aspects of the bids that are visible to suppliers, the termination of the bidding process, and the determination of an event winner. The typical closing rule in industrial online reverse auctions is that when a scheduled end time is reached, the event continues until a period of time passes in which no bidding occurs. As an example, if an auction is scheduled to end at 3 P.M., but bidding is still occurring at 2:58 P.M., the actual close time will be pushed back another five minutes until two minutes pass in which no bidding occurs. All the auction events included in this research use this type of closing rule. Thus, I now consider variations in (1) price visibility and (2) winner determination formats.

The visibility of bids refers to the degree to which bidders are able to view competitive bids.[5] In a full price visibility, or open-bid event, the bidders can see the bid of every supplier at every point in the auction event. However, this type of auction has several drawbacks because bidders may use the format to signal to others (which could encourage collusion), and bidding frenzies might encourage a winner's curse if suppliers overestimate the value of the contract. In addition, bidders do not need to bid as low as their private valuations if they observe that the level of bidding is much higher; their bids only need to be competitive.

Because of these shortcomings, many buyers have begun to use a partial visibility format, in which suppliers are not told the actual pricing levels but are given feedback only about their relative rank (whether they are the first-, second-, or third-lowest bidder) or are simply told the lowest bid price (and not the spread around this price) in real time. When suppliers do not know the exact level of the competitive bidding, they may be more compelled to bid to their bottom-line price to raise their probabilities of winning. In addition, when the buyer's goal is to identify the top three bidders to negotiate further with postauction, a partial visibility approach may be sufficient; there is no need to allow the low bidder to know how much lower its bid is than the second-lowest bidder (Carter et al. 2004).

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[4] The alternative is for the buyer to require the supplier to participate in individual bidding events for each product, which would make the bidding process more cumbersome.

[5] Visibility does not refer to the identity of the supplier. In virtually all online reverse auctions, bidders do not know the true identities of their competitors.

These partial visibility auctions are growing in popularity, and I contrast this format to full visibility auctions.

Full price visibility tends to be more detrimental to buyer–supplier relationships than no price visibility (Jap 2003). This is because price competition is explicit in the full visibility format, and the compressed time frame for bidding and the fast-paced nature of the event create a stressful context for suppliers. By making every bid visible to all bidders, suppliers reveal information about their private expectations of the value of the purchase contract. Together, these factors increase supplier bargaining costs and make the process so disagreeable that suppliers will accept renegotiation rather than persist with current pricing levels (Masten 1988). Full price visibility auctions tend to attract suppliers that seek market intelligence and hope to attract new business, but it may deter those that want to keep their pricing confidential and resent the pricing pressure of such formats. With partial price visibility formats, suppliers are able to maintain a level of confidentiality around their prices, and there is less explicit pressure to compete on this basis. Moreover, bidding momentum does not need to be lost in a partial price visibility auction. If a supplier recognizes that its bid is ranked fourth in an auction, the supplier can still be motivated to bid aggressively enough to improve its ranking. Given the opportunity for more information privacy and the preservation of bidding momentum, I expect that opportunism suspicions, overall satisfaction, and continuity expectations will improve with the use of partial price visibility auctions compared with full price visibility auctions because there is less revelation of private values and the format may be less stressful.

> P_4: Partial price visibility formats in online reverse auctions have a more positive impact on the interorganizational relationship than full price visibility formats.

Another key aspect of the auction mechanism is the rules for determining a winner, which I broadly classify into those that are buyer determined and those that are auction determined. Before the auction, suppliers are told that either the buyer retains full latitude to select the winner on any basis (this is the buyer-determined award rule) or the lowest or second-lowest price bidder in the auction will be declared the winner (this is the auction-determined award rule). The buyer-determined approach is often used when the intangible aspects of the product, such as quality, supplier reliability, and so forth, play a role in the procurement decision, whereas the auction-determined approach is more typical when the products are fairly comparable and the primary driver of the procurement decision is price.

The use of a buyer-determined or auction-determined award rule could affect the relationship in different ways. On the one hand, suppliers may believe that an auction-determined award is fairer and more explicit than a buyer-determined award. This belief arises because the supplier has information about the array of competitive bids and can understand how competitive its bid was in determining the award. On the other hand, with a buyer-determined award, buyers are able to view the whole array of bids and may pick the winning supplier on any basis; the buyer is not bound to choose the lowest bid as the winner. In this scenario, it is impossible to determine how the winning supplier is selected because, in general, suppliers do not receive feedback about how the buyer weighs various attributes in the selection process. Thus, the ability to map efforts onto outcomes has a positive impact on the relationship compared with the more ambiguous buyer-determined award rule. I expect that the use of an auction-determined award rule will lead the supplier to be less suspicious that the buyer is acting opportunistically, more satisfied with the overall relationship, and willing to stay in the exchange in the future because the mechanism for selection is explicit.

> P_5: Auction-determined award rules in online reverse auctions have a more positive impact on the interorganizational relationship than buyer-determined award rules.

A potential counterargument is that a buyer-determined award is preferable to an auction-determined award in that the buyer is better able to take the supplier's intangible benefits into account (e.g., prior experience and understanding of the buyer's operations, ability to work cooperatively with the buyer) and factor these benefits into the selection of a winning bidder. Thus, suppliers may believe that a buyer-determined award rule ensures a better representation of their true value to a buyer than an auction-determined award rule. If this is true, the logical consequence is that the buyer–supplier relationship would be improved when a buyer-determined award rule is used. This reasoning assumes that buyers have an accurate understanding of the differential value of each supplier, but this could be errorful. Because of this, I believe that auction-determined award rules have a more positive impact on the interorganizational relationship than buyer-determined award rules.

Event dynamics. The event dynamics, or price movement over the course of the auction, may not be directly controlled by the buyer, but they can have a significant impact on the subsequent buyer–supplier relationship. This is operationalized as the magnitude of the price savings that the auction generates. Although price savings are also a process outcome, they are a good indicator of event dynamics because they capture the magnitude of price variation. Stein, Hawking, and Wyld's (2003) recent case study describes the reaction of an incumbent supplier in an event. The supplier conducted research to identify the existing contract value ($1.6 million) and identified a bottom-line position (a margin of 12%). Within the first seven minutes, the reserve was driven down $90,000 (a 7% drop), and by the completion of the event, with only three bidders left, the lowest bid price dropped below the supplier's bottom-line position. "The managing director became caught up in the auction dynamic as he did not want to lose to other bidders," and by the end of the auction, the supplier's lowest bid had reduced its margin to 5%. "The managing director took about two weeks to get over losing to the competition" (Stein, Hawking, and Wyld 2003, p. 13). This scenario demonstrates how online reverse auction dynamics can demotivate and dishearten incumbent bidders.

In particular, participation in online reverse auctions may be more involving than face-to-face negotiations because of time compression, the availability of competitive pricing information, and the explicit level of competition. Bidders tend to focus on the electronic environment and forget the broader context of the marketplace and competitive context, thus giving a disproportionate amount of attention to the pricing aspect of the contract and overweighing its role in the buyer's sourcing decision. This dynamic, as indicated by a significant drop in price, can be alarming and can result in negative attributions about the other bidders and the buyer if the price drops to a level that is not credible (given the supplier's knowledge of the industry and competition). The supplier might infer that the buyer has included unqualified suppliers and is using the auction opportunistically to wrangle additional price concessions from it. This may have a demotivating effect on the supplier, lowering satisfaction with the overall relationship and expectations of continuing exchange in the future.

P_6: As the price savings in an online reverse auction increases, there is a negative impact on the interorganizational relationship.

Methodology

Procedure

The foregoing predictions are examined through the use of a quasi-experimental design (Cook and Campbell 1979) administered across the supply bases of four *Fortune* 100 firms in the automotive, chemicals, consumer products, and high-tech industries. Each firm was offered customized analyses and a summary report in return for its participation. Each firm identified between two and nine auction events and allowed me to survey suppliers before and after these events occurred. As an independent observer of these auction processes, I was not allowed to intervene in these events; for example, I was not able to create untreated control groups or matched pairs of events or to interview the participants.

Data collection. The data collection involved a nonequivalent quasi-experimental design using pretest and posttest measures from the same panel of suppliers. Because quasi experiments involve nonrandom assignment of the participants to conditions, I tried to enhance generalizability by replicating the design approach across 25 product categories. The buyers provided the names and e-mail addresses of suppliers invited to participate in an upcoming bid event and the auction design characteristics specific to their event. One week before the auction, suppliers were e-mailed an invitation to complete the pretest survey at a university Web site. The invitation also guaranteed individual anonymity and reassurance that the buyer would not have access to individual responses. Suppliers completed all items in reference to the specific buying organization and upcoming auction event; that is, they supplied perceptual measures of their relationship with the buyer. During the week following the auction, suppliers were sent an e-mail invitation to complete a posttest survey that contained essentially the same measures as the pretest survey. At the time of the posttest, suppliers in the auctions with buyer-determined award rules did not yet know whether they had won the auction event, which implies that their posttest scores are a direct function of the auction process. Each buying firm was also monitored to ensure that no major events or initiatives occurred at the time of the auctions that might disrupt or alter supplier perceptions and attitudes.

Sample. The total purchase contract value across the 25 auction events was $385 million. The products included various direct (e.g., hoses, pulleys, subassemblies, cables) and indirect (e.g., mechanical equipment, copy paper, pallets) materials.[6] The events varied in the nature and level of treatment effects. Specifically, the mean number of bidders across these events was 10.6 (SD = 7.5, range = 4–35). The average value of the purchase contract was $16 million (SD = $24 million, range = $880,000–$102.9 million), and the mean number of lots was 4.9 (SD = 3.7, range = 1–15). The average savings (the percentage drop in price over historical prices) generated from the auctions mean was 25% (SD = 18.9%, range = 0%–57%). Four events used an auction-determined award rule, and seven events used partial price visibility formats. This implies that 21 events used a buyer-determined award rule, and 18 events were full price visibility formats.

Respondents from supply organizations were the primary points of contact for the buyer; these people included senior executives, sales representatives, vice presidents, and business owners who handle large customer accounts. These people had the authority to make price concessions and determine major investment decisions. Two hundred sixty-four suppliers across the 25 events were invited to complete the survey, and 125 suppliers responded, generating a response rate of 61%. Of these respondents, 81 were incumbents, and the rest were new suppliers to the product category.

Because the propositions rely on supplier perceptions, respondent competency was assessed with both global and specific measures. The global measures included the number of years the respondent had been with the supplier firm and the number of years the respondents had been in their current positions. These means were 7.9 (SD = 6.8, range = .4–30) and 4.6 (SD = 4.2, range .25–21), respectively. The respondents also had extensive online reverse auction experience, having participated in an average of 12 (SD = 7.8, range = 4–35) auctions. Specific measures were also used to assess the respondents' knowledge of their firms' relationship with the buyer. Respondents were asked, "How knowledgeable are you about the following aspects?" The following statements were then listed below the question: "your firm's willingness to work with this buyer," "the state of your firm's relationship with this buyer," "your firm's willingness to invest in this customer," and "your firm's attitude toward this buyer." The mean response to these items on a seven-point scale (1 = "hardly knowledgeable," and 7 = "very knowledgeable") was 6.4 (SD = .7, range = 3.3–7). Collectively, these measures provide some confidence that the respondents were knowledgeable, relatively involved in the survey, and unlikely to have fabricated answers to the items. In other words, they were qualified key informants (Van Bruggen, Lilien, and Kacker 2002).

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[6] Indirect materials are goods that are not used in production, whereas direct materials are those that are used directly in the manufacturing process.

To minimize the possibility that respondents might try to create socially desirable responses and skew the results, I did not reveal the specific issues examined in this research and mixed up the multi-item measures to make it difficult for respondents to manipulate the data and my interpretations. Whenever possible, I also supplemented the survey data with additional interviews with various participants to obtain a richer sense of the organizational environment in which these auctions were being conducted.

Measurement

The interorganizational relationship is measured with multi-item scales (1 = "strongly disagree," and 7 = "strongly agree"). All the scales were adapted from prior research. Specifically, the scale items for overall satisfaction were adapted from the work of Ruekert and Churchill (1984), and the scale items for opportunism suspicions and continuity expectations were adapted from the work of Jap and Anderson (2003). Measures of overall satisfaction with the relationship and continuity expectations were completed by incumbent suppliers because new suppliers would have no basis for completing these measures. Table 1 provides an overview of the means, correlations, standard deviations, and reliabilities of these constructs, and the Appendix displays the specific items.

The mean value of opportunism suspicions is relatively low (M = 2.8, SD = 1.3, minimum = 1, maximum = 6). This value is not unusual, particularly in established relationships (Heide 1994). Although firms may devise relational safeguards to protect against opportunism, its presence in exchange is never zero (Williamson 1993). However, opportunism cannot be too high or else the parties would not transact.

A measurement model is estimated using maximum likelihood techniques in LISREL 8.54 (Jöreskog and Sörbom 1993). The model is composed of three first-order constructs of latent factors (opportunism suspicions, overall satisfaction with the relationship, and expectations of continuity), including the observable indicators, measurement errors, and intercorrelations between the constructs.

The chi-square fit index for the model is 311.61 (d.f. = 62). The comparative fit index and incremental fit index are .87, and the Tucker–Lewis index is .83. The root mean square error of approximation (RMSEA) is .19. Although comparative fit index, incremental fit index, and Tucker–Lewis index values of .9–1 are typically recommended, in sample sizes of less than 200, these indexes are unlikely to achieve this rule-of-thumb benchmark (Bearden, Sharma, and Teel 1982; Marsh, Balla, and Hau 1996; Marsh, Balla, and McDonald 1988). All the factor loadings and measurement errors are in acceptable ranges and are significant at $\alpha = .05$, providing evidence of convergent validity. Discriminant validity is stringently assessed with the procedure that Fornell and Larcker (1981) recommend. Each pair of constructs passes this test. Collectively, these indexes indicate a good fit of the model to the data.

Analysis

Because the predictions describe the impact of specific design variables on the relationship at large, I regress the predictors on the three aspects of the relationship (beliefs, evaluation, and expectations) collectively with a hierarchical multivariate analysis of variance and test for general effects. This test addresses the omnibus relationship between the two concepts and shows that it is consistent with theoretical assumptions. Having tested for the general effect, I then consider the individual effects to help understand what is driving the general result and inform the understanding of how they are related to the dependent variables of interest. This is done in a two-stage fashion in which covariates are estimated only in the first step, and then the main effects of auction design are added in the second step to give a clear understanding of the incremental variance explained by inclusion of the auction design variables.

The quasi experiments are a nonequivalent design, which means that the expected values of at least one characteristic of the groups are not equal even in the absence of a treatment effect. In other words, various factors could affect the posttest scores across the 25 events. I account for these differences by separating them from the treatment effects (e.g., the number of buyers and lots) using a multivariate analysis of covariance (MANCOVA) model in which the impact of the treatment effects is estimated for the group of interorganizational relationship characteristics, and various covariates are included to adjust for initial differences that could affect the posttest scores. These covariates include the purchase type, supplier type, and the respondent's pretest score. Purchase type is a dummy variable that reflects the type of materials purchased in the auction, whether they are materials used directly in the firm's manufacturing processes or indirect materials that are not used in the firm's product manufacturing efforts; two of the auctions procured indirect materials. Supplier type is a dummy variable that indicates whether the respondent represents an incumbent or a new supplier. The final covariate is the respondent's pretest score on the dependent variable of interest. The general form of the model is as follows:

TABLE 1
Construct Means, Correlations, and Reliabilities

Construct	M	SD	Minimum	Maximum	1	2	3
1. Suspicions of opportunism	2.37	1.10	1	6	**.92**		
2. Overall satisfaction with the relationship	4.80	1.04	2	7	–.41	**.87**	
3. Expectations of continuity	5.69	1.20	1	7	–.10	.34	**.84**

Notes: The –.10 correlation is not significant. Construct reliabilities are provided in bold in the matrix diagonal.

$$(1)\quad \text{Posttest score} = \alpha_0 + \beta_1\text{Number of bidders} + \beta_2\text{Contract value} + \beta_3\text{Number of lots} + \beta_4\text{Price visibility} + \beta_5\text{Award rule} + \beta_6\text{Price savings} + \beta_7\text{Supplier type} + \beta_8\text{Purchase type} + \beta_9\text{Pretest score} + \varepsilon_1,$$

where

Posttest score = interorganizational relationship aspects (i.e., opportunism suspicions, overall satisfaction, and continuity expectations),
Number of bidders = the number of a specific event,
Contract value = the dollar amount of the purchase contract,
Number of lots = the number of lots in a specific event,
Price visibility = dummy for full visibility (0) and partial visibility (1),
Award rule = dummy for buyer-determined (0) and auction-determined (1),
Price savings = percentage of price savings generated by a specific event,
Supplier type = dummy for current suppliers (0) and new suppliers (1),
Purchase type = dummy for direct materials (0) and indirect materials (1),
Pretest score = the value of the supplier attitude toward the auction or buyer before the auction,
α_0 = the intercept,
β_{1-9} = the coefficients for the auction structure elements and covariates, and
ε_1 = the error term for the model.

This model matches the covariates to the predicted posttest value for all levels of the auction design elements and examines the differences between them. Note the inability to account for potential dependencies among supplier responses in a specific auction because of the limited sample size. A Breusch–Pagan test for heteroskedasticity was not significant ($\chi^2_{(1)} = 1.18$, $p < .28$), indicating that heteroskedasticity may not be problematic in this sample. A clustering of observations and estimation through a Huber–White sandwich estimator of variance is inconclusive, because each auction is treated as an independent observation and the resulting statistical power is low. It is also not possible to estimate a fixed-effects model because of collinearity with the design variables, and I did not have suitable data for an instrumental variable estimation approach.

Some readers might be concerned that suppliers would be naturally biased in their attitudes toward the buyer or auction. For example, suppliers may regularly suspect buyers of being opportunistic or may overstate their willingness to be responsive or their expectations of the future. Such biases would increase the observed scores. Even so, it is important to note that such biases would operate within both the pretest and the posttest but would not explain a significant relationship between the scores, which is the focus of this research.

Results

Table 2 displays an overview of the Stage 1 and 2 results. In the first stage, the covariates of purchase and supplier type and the pretest scores account for 26%, 7%, and 3% of the variance in opportunism suspicions, overall satisfaction, and continuity expectations, respectively. However, the Stage 2 results indicate that when the effects of auction design—the number of bidders, economic stakes, and auction mechanism—are added to the regression, the variance explained jumps to 51% for opportunism suspicions, 29% for overall satisfaction, and 18% for continuity expectations, suggesting that auction design (and the resulting experience from the design choices) plays a significant role in explaining interorganizational outcomes.

Test of Predictions

P_1 considers the relationship between the number of bidders and the interorganizational relationship. The MANCOVA indicates that, in general, the effect of the number of bidders and the interorganizational outcomes is positive and significant ($F_{3,\,111} = 16.84$, $p < .0001$), which does not support P_1. To understand this effect better, I find that the number of bidders has a significant, positive impact ($\beta_1 = .05$, $p < .01$) on opportunism suspicions, consistent with my prediction that increasing the number of bidders increases participation and may be viewed as the buyer opportunistically attempting to squeeze further price concessions from suppliers. It is surprising that the number of bidders had a significant, positive impact ($\beta_1 = .05$, $p < .01$) on satisfaction. It could be that when suppliers recognize that there are a critical mass of bidders that can quote competitively, they perceive the buyer as doing its due diligence to keep its procurement prices in check; indeed, a few other suppliers may be a credible signal that the buyer knows the other realistic alternatives and has included those suppliers in the event.[7] However, this argument suggests that too few or too many bidders is not credible. Thus, I estimate a regression in which I add a curvilinear effect of the number of bidders; this parameter estimate is positive and significant (β_{12} = .01, $p < .00$). A plot suggests that satisfaction increases as the number of bidders increases to approximately 12.2 bidders per event on average and then drops thereafter, consistent with this possibility.

P_2 and P_3 examine the impact of the contract value and number of lots on the interorganizational relationship. The MANCOVA indicates that the value of the event has a positive, significant impact ($F_{3,\,111} = 3.04$, $p < .03$) on the inter-

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[7] In independent interviews with suppliers, they reported that when they know that there are only two to three alternative suppliers in the world and then find five or six suppliers bidding in the auction, they suspect that the buyer has included some unqualified bidders to drive down the price unfairly. In this sense, the number of suppliers can be an important indicator of the buyer's opportunism.

TABLE 2
Hierarchical Regression Results

	Posttest Dependent Variables					
	Opportunism Suspicions		Overall Satisfaction		Continuity Expectations	
Stage 1 Regressions	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	2.48	.81**	4.77	.76***	6.27	.57***
Supplier type	–.42	.23*	.33	.22	–.13	.16
Purchase type	.64	.39	–.63	.70*	–.45	.28
Pretest opportunism suspicions	.50	.11***	–.09	.10	.00	.08
Pretest overall satisfaction	.18	.12	.12	.12	.08	.09
Pretest continuity expectations	–.32	.09***	.00	.09	.01	.07
R^2	.26		.07		.03	
Stage 2 Regressions						
Intercept (β_0)	2.07	.73***	4.05	.75***	5.24	.58***
Number of bidders (β_1)	.05	.01***	.05	.01***	.00	.01
Contract value (β_2)	–.01	.01	.02	.01***	.01	.01***
Number of lots (β_3)	.09	.03***	–.07	.03**	.06	.03**
Partial price visibility (β_4)	.47	.32	1.02	.33***	–.11	.26
Winner determination (β_5)	.16	.43	.14	.44	.37	.34
Price drop (β_6)	.00	.01	–.02	.01***	.00	.00
Supplier type (β_7)	.19	.21	.16	.22	–.13	.17
Purchase type (β_8)	.43	.47	–.33	.48	–.58	.37
Pretest opportunism suspicions (β_9)	.21	.10**	–.04	.10	–.04	.08
Pretest overall satisfaction (β_{10})	–.01	.11	.15	.11	.01	.09
Pretest continuity expectations (β_{11})	–.28	.10***	.14	.10	.16	.08**
R^2	.51		.29		.18	

*$p < .10$.
**$p < .05$.
***$p < .01$

organizational relationship overall, as does the number of lots ($F_{3,\,111} = 8.95$, $p < .0001$), in support of P_2 and P_3. The Stage 2 regressions indicate that these effects are due to a significant, positive effect of the contract value on overall satisfaction ($\beta_2 = .02$, $p < .01$) and continuity expectations ($\beta_2 = .01$, $p < .01$), consistent with my expectations that as the economic stakes increase, the impact on the relationship is more positive. It is surprising that the impact of number of lots is mixed. There is a significant, positive effect of the number of lots on opportunism suspicions ($\beta_3 = .09$, $p < .01$) and continuity expectations ($\beta_3 = .06$, $p < .03$) but a significant, negative effect on overall satisfaction ($\beta_3 = -.08$, $p < .03$). It may be that the positive effect of lot number (i.e., the creation of more and varied opportunities for participation) is limited; that is, beyond a certain range, more lots make the bidding task cumbersome. To assess this possibility, I add a curvilinear effect of the number of lots to the regression. This term has a positive, significant impact ($\beta_{12} = .02$, $p < .01$) on continuity expectations and a significant, negative effect on opportunism suspicions ($\beta_{12} = -.01$, $p < .04$). A plot reveals that the impact of the lot number reaches its nadir at seven lots for opportunism suspicions and peaks at six lots for continuity expectations.

P_4 suggests that partial price visibility formats are positively related to the interorganizational relationship. The results support this prediction; there is an overall significant, positive impact ($F_{3,\,111} = 3.38$, $p < .02$) of partial price visibility formats on interorganizational outcomes. The Stage 2 results indicate that partial price visibility formats have a significant, positive effect on overall satisfaction ($\beta_4 = 1.02$, $p < .01$). Consistent with this, a Duncan multiple range test of mean differences reveals significant differences in the levels of overall satisfaction across full and partial price visibility formats. Specifically, overall satisfaction with the relationship is higher in events with partial visibility formats (5.38) than in events with full price visibility formats (4.64). A regression that breaks out the two types of partial visibility formats suggests that the positive impact on satisfaction is primarily driven by the rank format ($\beta_{12} = 1.17$, $p < .01$) and is only marginally related to the low-price format ($\beta_{13} = .91$, $p < .10$).

P_5 considers the possibility that winner determination rules affect the interorganizational relationship. There is no significant empirical support ($F_{3,\,111} = 1.65$, $p < .18$) for this prediction in the MANCOVA, and its effect was not significant in all the individual regressions.

P_6 suggests that the price savings generated over the course of the online auction event are negatively related to the interorganizational relationship. The results support this prediction; there is a significant, negative effect ($F_{3,\,111} = -3.87$, $p < .01$) of the drop in price on interorganizational outcomes. The Stage 2 regressions indicate that this may be due to a significant, negative impact ($\beta_6 = -.02$, $p < .01$) on overall satisfaction.

Potential Interactions with Winner Determination Rules

The preceding results suggest that winner determination rules are not related to outcomes. I consider the possibility that winner determination rules could interact with various auction design characteristics further to affect opportunism suspicions. For example, it may be that auction-determined award rules are viewed as fairer than buyer-determined award rules because winner determination is more explicit (low price). In contrast, in buyer-determined auctions, bidders would compete more aggressively on nonprice attributes, such as relationship- or trust-building activities, and could use the auction to their advantage (e.g., survey prices without bidding aggressively). This would imply that the negative impact of number of bidders and full price visibility formats might be mitigated in auction-determined events because the selection of a winner is explicit. By this same reasoning, the positive impact of higher auction stakes (i.e., the number of lots and contract value) could be enhanced in auctions in which winners are determined by price alone.

When the three interaction terms are added to the regressions, the R-square of opportunism increases to .56 (from .51 without the interaction terms). The interaction of award rule with number of bidders is not significant (β_{12} = –.06, $p < .84$). The interaction of award rule with number of lots and price visibility attributes is significantly related to opportunism suspicions. Specifically, the results suggest that the use of auction-determined award rules and an increasing number of product lots are negatively related (β_{12} = –.52, $p < .02$) to suspicions of opportunism, suggesting that more lots provide more opportunities to participate and allow for specialization, which, together with the explicit award rule, improves perceptions of fairness. However, the use of auction-determined award rules and full price visibility formats are positively related to opportunism suspicions (β_{12} = 2.48, $p < .05$). It may be that the use of auction-determined award rules is unable to mitigate the negative impact of full price visibility competition, and instead the combination of these two attributes heightens suspicions of opportunism. This is consistent with the possibility that the explicit nature of the auction format, in terms of both how the winner is selected and the full range of information on bids, creates a price focus at the expense of intangible attributes, such as quality, responsiveness, and other forms of buyer support.[8]

Potential Interactions with Supplier Type

I also consider the possibility that interactions exist between supplier type and auction design effects, such as the event value, number of bidders, and price drop. For example, as the value of the event increases, incumbents may be more motivated to participate, thus increasing their satisfaction and responsiveness toward the buyer. Incumbents may also be more threatened as the number of bidders increases, thus having an adverse effect on interorganizational outcomes. As the price drops, incumbents may feel more threatened than new suppliers. However, none of these interactions have a statistically significant impact on the interorganizational relationship.

Discussion

Collectively, the results demonstrate that online reverse auction design through the participants, stakes, format, and event dynamics are systematically related to interorganizational outcomes, suggesting that the buyer's auction design choices can be an important strategic variable in managing its relationships with the supply base. The analysis points to four key results.

First, as the number of bidders in an online reverse auction increases, participation, bidding, and savings in the auction increase, creating pressure on suppliers to lower their margins to retain or win new business. Thus, suspicions of opportunism increase because suppliers infer that the buyer has made a strategic choice to raise the level of price competition (and increase the likelihood of lower supply margins). In addition, the number of bidders, up to approximately 12 bidders per auction, has a positive impact on overall satisfaction. It may be that the number of bidders provides a credible signal to suppliers that the buyer invited credible supply alternatives to the auction. Beyond this point, an increase in the number of bidders may suggest to suppliers that some bidders are unqualified supply sources and are included only to drive price down unfairly, and as a result, satisfaction is adversely affected.

Second, stakes matter; as the size of the purchase contract increases, the interorganizational relationship is enhanced through heightened overall satisfaction and continuity expectations. This can happen by purchasing greater volumes, enabling suppliers to recoup any margin losses through economies of scale. In addition, increasing the number of lots provides multiple opportunities for suppliers to participate in the event and provide compelling purchase configurations for the buyer within limits. By having approximately six to seven lots in an event, the buyer can decrease opportunism suspicions and improve continuity expectations. With too few lots, the economic stakes are not worthwhile, and with too many lots, the bidding task becomes cumbersome.

In addition, I find that though the main effect of award rule is not significantly associated with interorganizational outcomes, its impact is contingent on other factors, such as the number of lots in an auction. In this case, as the number of lots increases and an auction determined award rule is used, opportunism suspicions are reduced. This may be due to the increased opportunities for suppliers to participate and specialize as well as a clear mapping of how winners are selected. The net result of all these effects may be to improve the supplier's disposition toward the buyer, its willingness to be supportive, and its expectations of the future.

Third, partial price visibility formats in online reverse auctions are gentler on the interorganizational relationship and have a greater impact on overall satisfaction than full price visibility formats. It may be that an intermediate level of price visibility is less threatening in that the supplier's specific bids are not available to competitors; thus, the supplier's private thoughts about the true market value of the contract are not revealed. Consistent with this, suppliers in the partial price visibility condition have lower suspicions of opportunism, and the incumbent's overall satisfaction with the relationship is significantly greater than that of suppliers that participated in full price visibility auctions. The overall pattern of results is consistent with that of Jap (2003), who compares full price visibility formats with no price visibility (sealed-bid) formats and finds that full price visibility formats can adversely affect the interorganizational relationship.

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[8] As a check, I considered whether the interactions of award rule and design characteristics were related to overall satisfaction or continuity expectations, but these effects were not significant.

Despite these positive effects, there is a dark side to these auctions. The results suggest that increasing the number of bidders or having too few or too many lots can raise opportunism suspicions. In addition, the use of an auction-determined award rule together with full price visibility bidding formats can hurt relationships by raising suspicions of opportunism. Collectively, these effects may be due to the notion that online reverse auctions are never completely transparent: Bidders never know exactly who they are competing with or the specific motivation behind how and why various lots are grouped together. This "noise" in the system, particularly when compounded by a focus on price, may lead suppliers to assume that the buyer is using these conditions to its advantage. More research into the effectiveness of various bidder selection, lotting strategies, and alternative award rules would enhance the understanding of these aspects.

Fourth, the auction event dynamics can affect the buyer–supplier relationship. Specifically, the more the price drops in an event, the more significantly negative is the impact on the relationship. High cost savings in an online reverse auction event may translate into decreased margins for suppliers and reduced supply opportunities because the price level prohibits their ability to supply the buyer effectively. Incumbent suppliers may believe that the buyer is using the auction to opportunistically wrest price concessions from them, thus reducing their overall satisfaction with the buyer. To my knowledge, this is the first study to show that the price dynamics in an event affect the interorganizational relationships related to the event. This underscores the notion that technology-enabled processes do not operate in isolation but can have a systematic impact on auction participants' beliefs, expectations, and current performance.

Limitations

There are limitations to the research. For example, this study could have considered many more aspects of online reverse auction design and many more interorganizational outcomes, but this work represents a first step in better understanding the interface between online technologies and the interorganizational relationship. However, much remains to be considered. Another limitation might be that the research considers only the perspective of the supplier and does not account for the buyer's perspective. A dyadic approach would have been preferable, though the participating companies would not allow this option.

Still another limitation includes the types of data I was able to glean from the field sites. For example, I was not able to determine and incorporate information about the actual winner or loser of each event into the analysis. It would have been helpful to control for this aspect in auctions using an auction-determined award rule. In the case of buyer-determined auctions, it can often take four to six weeks to determine the final winner. Thus, this delay actually enabled a clearer understanding of the impact of the auction process on interorganizational outcomes. Another example of data that would have been beneficial to this study is process measures, such as the number of bids submitted by a particular bidder, the rate of price declines, the length of the bidding process, and so forth. However, the availability of such data was limited by the field sites.

A final limitation is the sample size. It would have been helpful to survey many more suppliers across more product categories, industries, and environments. However, the quasi-experimental approach requires an extraordinary amount of effort to administer surveys before and after the auction events because auctions are regularly scheduled (and rescheduled) and reconfigured over time. Furthermore, because the auctions contain data about a sensitive issue—namely, the buyer's procurement pricing—they require a high level of clearance and endorsement from the buying organization to observe and obtain these data.

Implications for Management

An ongoing challenge in many buying organizations is the incorporation of e-commerce tools, such as online reverse auctions, into a coherent sourcing strategy. At one level, buyers wrestle with pressure from upper management to secure the lowest price possible, but they must also understand the valuable role of long-term relationships and strategic partnerships. It is becoming increasingly clear that success in industrial sourcing will be inherently linked to the success of the supply base and the struggle to balance new opportunities and emerging technologies with long-term results.

In general, buyers should strive for events with large contract values and use partial price visible formats to safeguard their supply relationships. This approach provides the financial motivation to participate and some level of pricing confidentiality without necessarily needing to sacrifice bidding aggressiveness.

However, the current research suggests that conducting online reverse auctions that preserve interorganizational relationships is a delicate balancing act. To avoid raising opportunism suspicions, buyers must consider the number of suppliers and lots. Too few or too many suppliers or lots will have damaging effects on their supply relationships. Opportunism suspicions can also be avoided by coupling auction-determined award rules with a large number of lots or partial price visibility formats.

Finally, the event dynamic can play a critical role, and this may be largely beyond the buyer's control. Specifically, although the buyer can attempt to preserve and enhance its relationships with the supply base through auction design, the use of these auctions exposes a key trade-off between price savings and supply relationships (see Jap 2003). The greater the price savings extracted in these auctions, the more likely the relationships will be adversely affected. The challenge is for buyers to manage the process such that enough savings can be generated to make the process worthwhile from their perspective, while cushioning the impact on the interorganizational relationship through smart design.

Directions for Further Research

This research represents a starting point for future work on the impact of online reverse auctions on buyer–supplier relationships. A fruitful avenue for research would be to evaluate the long-term implications of using multiple online reverse auctions on actual supplier behavior and performance over time from the buyer's perspective. Can the use of online reverse auctions improve relationships over time by adding a sense of fairness and objectivity to the industrial sourcing process, or do the auctions create resentment, undermine motivation, and encourage retaliation in the long run?

Another important direction would be to understand better what leads suppliers to bid aggressively in online reverse auctions. It is possible that "smart" aggressive bidding—bidding aggressively when there is a true payoff from doing so as opposed to bidding aggressively because of an overestimation of the contract (i.e., the winner's curse) or getting caught up in the bidding fever—could have a less negative effect on the interorganizational relationship. These issues and more are worthy of additional investigation.

Collectively, the results of this research indicate that the structure and design of online reverse auctions can exert complex relational effects on suppliers. Technology does not exist in isolation; its value in organizational contexts is fundamentally tied to the participants who interact with the technology in computer-mediated environments. By illuminating the interplay between technology and the psychological effects on organizational participants, I have provided evidence of these effects and guidance on how to improve the design and structure of online reverse auctions.

Appendix: Scale Items

Suspicions of Opportunism

How likely is it that the buyer firm would do the following: (1 = "very unlikely," and 7 = "very likely")

- Make false accusations.
- Provide false information.
- Expect your firm to pay for more than their fair share of the costs to correct a problem.
- Make hollow promises.
- Be unwilling to accept responsibility.
- Be aloof toward your firm.
- Fail to provide proper notification.
- "Window-dress" their efforts to improve.

In the items that follow, "They" refers to the buyer firm, and "We," "Our," and "Us" refer to your firm. Please indicate the extent to which you agree or disagree with the following statements: (1 = "strongly disagree," and 7 = "strongly agree")

Overall Satisfaction with the Relationship

- Our relationship with them has more than fulfilled our expectations.
- We are satisfied with the outcomes of our relationship.
- Our relationship with them has been a successful one.

Expectations of Continuity

- We expect to continue working with them on a long-term basis.
- Our relationship with them will last far into the future.

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Nicholas H. Lurie & Charlotte H. Mason

Visual Representation: Implications for Decision Making

A large number of visualization tools have been created to help decision makers understand increasingly rich databases of product, customer, sales force, and other types of marketing information. This article presents a framework for thinking about how visual representations are likely to affect the decision processes or tasks that marketing managers and consumers commonly face, particularly those that involve the analysis or synthesis of substantial amounts of data. From this framework, the authors derive a set of testable propositions that serve as an agenda for further research. Although visual representations are likely to improve marketing manager efficiency, offer new insights, and increase customer satisfaction and loyalty, they may also bias decisions by focusing attention on a limited set of alternatives, increasing the salience and evaluability of less diagnostic information, and encouraging inaccurate comparisons. Given this, marketing managers are advised to subject insights from visual representations to more formal analysis.

Marketing managers and consumers have more information than they know what to do with. High-speed land and wireless networks, scanning and tracking technology, and large data warehouses offer increasing opportunities for managers to monitor and respond dynamically to changing market conditions (Alba et al. 1997; Blattberg, Glazer, and Little 1994). Product comparison Web sites, Web-based discussion groups, and online retailers provide consumers with easy access to product information and reviews to help them choose from an ever-expanding range of products and services. However, the benefits of all this information are often not realized, because managers and consumers are increasingly overloaded with information in electronic environments (Farhoomand and Drury 2002; Lurie 2004; Schwartz 2004).

Much of the information that managers and consumers receive is symbolic in nature, consisting of numbers and text. Processing this kind of information is inherently effortful because it involves rule-based reasoning, in which data are abstracted into values that, in turn, are given meaning through formal rules and deliberative analysis (Sloman 1996). At the same time, humans have evolved great visual and spatial skills, including the ability to detect edges and discontinuities, things that stand out, variations in color and shape, and motion; to recognize patterns; and to retrieve information using visual cues (Kosslyn 1994). This suggests that a solution to information overload could be to present information in ways that engage the use of the associative system, in which meaning is ascribed through gestalt and automatic processes, such as visual recognition (Sloman 1996). By drawing on humans' highly developed skills of perceptual sense making, the old adage that "a picture is worth a thousand words" may be replaced with "a picture is worth a thousand rows [of data]" (Youngworth 1998).

Importantly, the same complex technological innovations that enable the collection and dissemination of massive amounts of information have led to tools that promise to help decision makers reduce large data sets to simple visuals. These visualization tools range from common bar graphs to sophisticated virtual environments. Information visualization offers a way to shift cognitive load to the human perceptual system through graphics and animation (Lohse 1997; Zhang and Whinston 1995). Visual representations can enlarge problem-solving capabilities by enabling the processing of more data without overloading the decision maker (Tegarden 1999).

Although visualization tools are increasingly available to consumers (e.g., Fidelity Investments's [2006] visual map of the stock market from SmartMoney.com) and there is growing interest from managers and academics, particularly among researchers in information technology (Card, Mackinlay, and Schneiderman 1999), little is known about the implications of such tools for marketing managers and consumers. Vendors claim that their tools will lead to better, faster, and more confident decisions, and indeed there is some anecdotal evidence that these tools can make a difference (Borzo 2004; Esfahani 2005; Miller 2004). However, there has been little systematic analysis of the implications of these tools for decision making.

Visualization tools are particularly common in fields such as genetics and biology (Kraemer and Ferrin 1998; Montgomery et al. 2004), as well as medicine (Sinha et al. 2002; Trelease 2002), but business applications are said to lag the sciences by as much as ten years (West 1995). More

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important, the aspects of common interest to information technology researchers, such as speed and accuracy on well-defined and simple tasks (Bederson et al. 1998; Byrne 1993; Kobsa 2001; Plaisant 2004), provide few insights into the potential implications of visual representation for decision-making processes and outcomes in field settings in which data exploration and discovery are necessary (Cleveland 1987). In this article, we present a framework of how visual representations are likely to affect the decision processes or tasks that marketing managers and consumers commonly face, particularly those that involve the analysis or synthesis of substantial amounts of data. Within this framework, we develop a set of testable propositions that serve as an agenda for further research.

Visual Representation

Early work extending visual representation beyond simple charts and graphs found that graphic displays enable scientists to "make use of the uniquely human ability to recognize meaningful patterns in the data" and to see "patterns in data that would never have been picked up with standard statistical methods" (Kolata 1982, p. 919). Among scientists, graphic representations increased in popularity with greater acceptance of empirical, as opposed to rational, approaches in which evidence, not just theory, drove scientific investigation (Wainer and Velleman 2001). Importantly, the scientific revolution that began in the eighteenth century was accompanied by a change in how graphics were created, from being almost fully deductive and driven by theoretical models to empirical approaches based on the display and interpretation of observed data (Wainer and Velleman 2001).

Researchers have used the terms "information visualization" (Card, Mackinlay, and Shneiderman 1999), "data visualization" (Green 1998), and "scientific visualization" (DeFanti, Brown, and McCormick 1989) to refer to the presentation of information in visual form. These terms are not mutually exclusive and are not always used consistently. Distinctions among these terms are often based on whether the underlying data are numerical or nonnumerical, whether the data are tied to physical or abstract attributes, whether absolute or relative values of data are represented, and the number of variables that are simultaneously represented. Another form of visualization is virtual reality, in which a computer display simulates a three-dimensional, interactive visual environment. In this article, we use the term "visual representation" to encompass these various forms of visualization. Specifically, visual representation involves the selection, transformation, and presentation of data (including spatial, abstract, physical, or textual) in a visual form that facilitates exploration and understanding. We use the term "visualization tool" to refer to a specific implementation, including software applications, of visual representation.

Visualization tools are an intermediate step in converting data into insight (Green 1998). Data characteristics such as dimensionality (both the number of cases and the number of variables), scale (categorical, ordinal, and metric), and cardinality (e.g., binary versus "massively categorical variables") affect which tools are appropriate. Although different visualization tools use different algorithms, all implicitly or explicitly preprocess the raw data. Visualization techniques include using color, size, shape, texture, orientation, and brightness to portray some dimensions; distortion approaches to highlight some data while providing context; graphic portrayals of hierarchical and network relationships; and interactivity (Green 1998).

Importantly, these transformations potentially affect the ultimate insights derived from the data. By changing the presentation of information, visualization tools have implications for both decision processes and outcomes (Bettman and Kakkar 1977). For example, visual representations may make it easier to see patterns and outliers, make certain information more salient and other information less salient, and show detailed information on specific alternatives or provide a context for evaluating focal information. This may improve decision quality. At the same time, visual representations may accentuate biases in decision making and lower performance by increasing attention to particular attributes or less diagnostic information (Glazer, Steckel, and Winer 1992; Jarvenpaa 1990; Mandel and Johnson 2002).

Drawing on prior research in information technology and computer science, as well as decision making and marketing, we focus on two characteristics of visual representations that are particularly likely to affect marketing managers and consumers: (1) the "visual perspective," which is determined by task variables, such as whether a representation can be manipulated by the user (i.e., its interactivity) and the extent to which a representation allows the user to see contextual and/or detail information (i.e., the depth of field), and (2) the "information context," which is determined by context variables that affect the vividness, evaluability, and framing of information. Task variables are general characteristics of information environments, including how much information is presented and how the decision maker can interact and respond to information, whereas context variables refer to data values, colors, and shapes specific to a given decision problem (Bettman et al. 1993; Lurie 2004). Each of these has important implications for how decision makers access and process information and make decisions. For example, in terms of visual perspective, interactivity may enhance realism and, therefore, the extent to which visual representations substitute for terra firma information search (Burke 1996; Burke et al. 1992), and depth of field may change the number of alternatives considered and the perceived differences among choice alternatives. In terms of information context, the effects of alternative visualizations on vividness and evaluability may change the relative ease with which different attributes may be compared and, therefore, choice outcomes (Hsee 1996).

Table 1 provides examples of commonly available visualization tools with applications for marketers and consumers. For each tool, Table 1 indicates whether it affects the visual perspective and/or the information context.

We propose that the visual perspective and information context influence decision processes and outcomes by changing the decision-making frame—that is, what information a decision maker uses and how he or she uses it to

TABLE 1
Examples of Visualization Tools

Visualization Tool	Characteristics Affected	
	Visual Perspective	Information Context
TableLens (http://www.inxight.com/products/sdks/tl/) TableLens creates a visual representation of large amounts of tabular (e.g., spreadsheet) data, including an interactive interface that enables the user to sort columns, expand and contract rows, and drill down for more details.	✓	
SmartMoney.com's MarketMap (http://www.smartmoney.com/marketmap/) A Treemap (i.e., a two-dimensional representation of hierarchical data in which each element is represented by a cell whose arrangement, size, and color represent attributes of that data element) application used for the reporting of stock portfolio information.	✓	✓
Newsmap (http://www.marumushi.com/apps/newsmap/newsmap.cfm) A Treemap application that visually reflects patterns in news reporting.	✓	✓
ArcGIS (http://www.esri.com/products.html) Geographic information software used for business-mapping applications, such as displaying results by sales territory or other regions.		✓
Lands' End's My Virtual Model (http://www.landsend.com/) An interactive virtual reality application that enables customers to build a virtual image of themselves and then "try" on clothing.	✓	
Fish-Eye Visualizations Nonlinear magnification enables the user to see details of immediate interest (i.e., focus) and the overall picture (i.e., context). Examples include maps, charts, and text-based applications.	✓	

Notes: Table 1 identifies which characteristics of visual representation a given tool is likely to affect: (1) the visual perspective (i.e., interactivity or depth of field) or (2) the information context (i.e., vividness, evaluability, or framing).

gain insights and make decisions. Figure 1 provides an overview of the aspects of visual representations, outcome variables, and associated propositions that are the focus of this article. Although these aspects are by no means exhaustive, they offer a starting point for understanding how visual representations are likely to affect the decisions of marketing managers and consumers. In this article, we focus on main effects of visual representations. For completeness, Figure 1 also includes user characteristics that are likely to moderate the proposed main effects on decision-making processes and outcomes. We examine some of these in the "General Discussion" section. However, for brevity, we limit our discussion and do not develop formal propositions about these moderators.

Visual Perspective

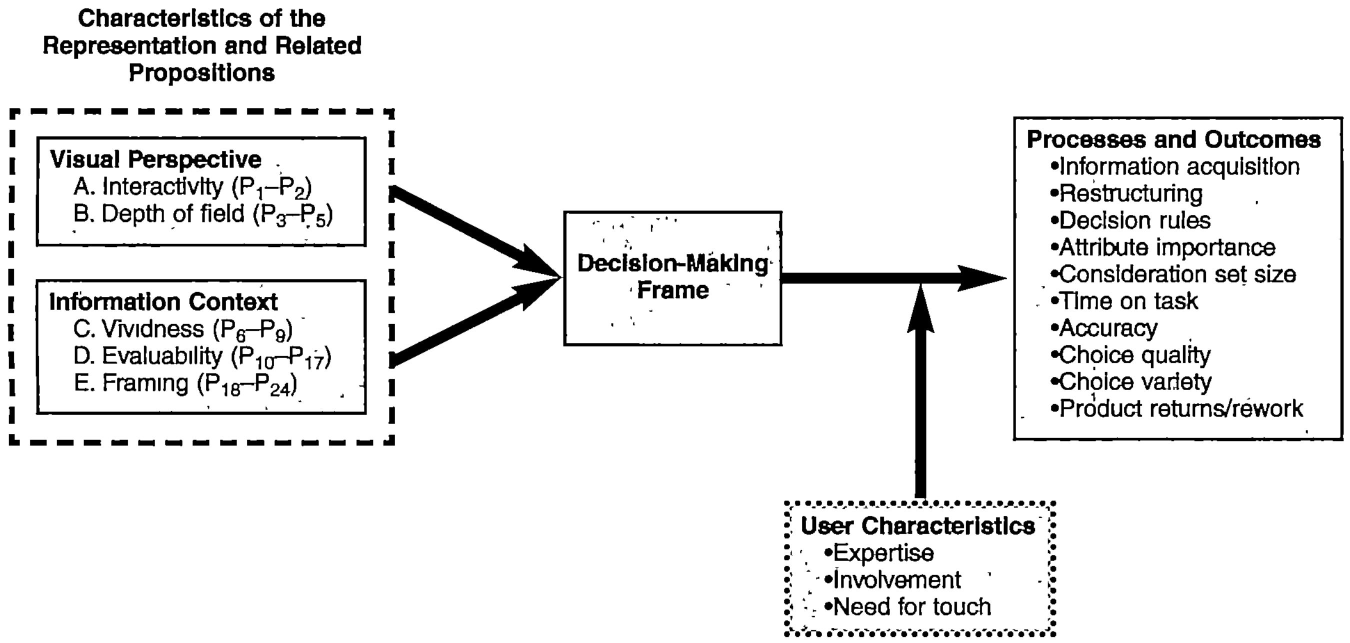
We use the term "visual perspective" to refer to how a given visual representation changes the relationship between visual information and the decision maker. The first aspect of visual perspective is "interactivity," or the user's ability to change perspective, for example, by rotating or simulating movement around an image. The second aspect of visual perspective is "depth of field," which refers to whether a tool provides context by displaying an overview of large numbers of data points and/or more focused detail information on particular data points of interest.

Interactivity

Interactivity distinguishes many current visualization tools from more traditional graphic representations. Such tools enable the user to restructure the representation of information (Coupey 1994) by interactively changing which variables are shown, cut points for displaying variables, and whether particular variables are shown by colors or shapes. For example, Spotfire's DecisionSite (2006) enables the user to determine interactively which variables to display and the range of values shown. Other tools allow users to group objects and move selected objects into focus (Chuah et al. 1995) or to prune information from display (Kumar, Plaisant, and Scheiderman 1997). By giving users increased control over the information flow (Ariely 2000), interactive visualization tools have important implications for decision making.

By enabling decision makers to restructure the information environment, interactive visualization tools may create a better match between the task and the decision environment, which should improve decision quality and/or reduce the effort required (Eick and Wills 1995). Because restruc-

FIGURE 1
Characteristics of Visual Representations and Implications for Decision Making



Notes: This figure proposes that characteristics of visual representations, including the visual perspective (interactivity and depth of field) and information context (vividness, evaluability, and framing), combine to form the decision-making frame, which in turn has implications for decision-making processes and outcomes. Figure 1 includes a partial list of these processes and outcomes. User characteristics, such as expertise, involvement, and need for touch, are proposed to moderate the effect of the decision-making frame on processes and outcomes. For example, expertise is likely to moderate the extent to which interactivity leads to greater information restructuring (see the "General Discussion" section)

turing leads to more compensatory decision making but is contingent on the effort involved (Coupey 1994), interactive visualization tools that lower the cognitive cost of restructuring information can also lead to more compensatory processing. This suggests that marketing managers using interactive visualization tools will be more likely to consider multiple factors than managers using traditional reports.

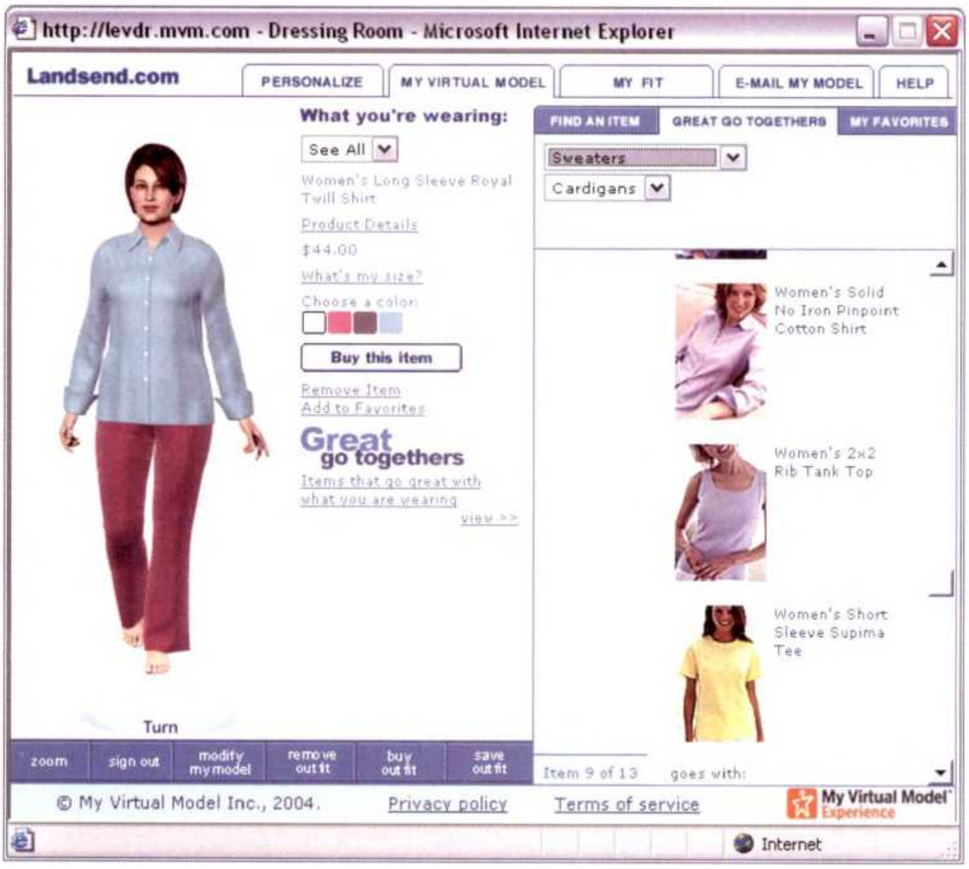
In addition to information restructuring, many visualizations allow decision makers to interact with the visual representation. An increasingly common interactive visualization tool, particularly for consumer marketing, is virtual reality, in which a real or imagined environment is visually simulated (potentially with sound, motion, and other effects) and explored interactively. Sprint's (2006) 360-degree views of telephones and Volkswagen's (2006) full-motion tour enable users to walk around or through a product. Others, such as Nike's (2006) iD, Trek's (2006) Project One, Lands' End's (2006) My Virtual Model (see Figure 2, Panel A), and La-Z-Boy's (2006) room planner, allow users to create and see customized products, to see what they would look like in a particular outfit, or to see how new furniture would look in their homes. Interactive virtual reality tools can also be used to test new products (Urban et al. 1997; Urban, Weinberg, and Hauser 1996) and to examine the effects of alternative promotion, display, and pricing schemes (Burke 1996; Burke et al. 1992).

By mimicking the act of touching and feeling products, interactive virtual reality visualizations may be better substitutes for haptic experiences than textual information. This is likely to increase consumers' confidence in their choices and lower the proportion of physical search relative to online search. For example, a couple buying a house may first use traditional (text) online information to screen alternatives and then virtually "visit" more houses than they otherwise would have physically visited. Virtual reality tools may also enable them to screen out more houses before physically visiting them.

By making users more comfortable, interactive virtual reality tools can increase product trial and adoption (Ganapathy, Ranganathan, and Sankaranarayanan 2004; Urban et al. 1997). In support of this, a recent report shows that Lands' End's online customers who use My Virtual Model have a 34% higher conversion rate and an 8% higher average order value (Miller 2004). Similarly, users of Restoration Hardware's eCatalog viewer, which enables customers to design furniture and lighting, have twice the conversion rates of those who use the traditional Web interface, and Timberland's Boot Studio, which allows shoppers to customize their boots, gets three times as many hits and higher conversion rates than the basic Web site (Esfahani 2005; Scene7 2005). In addition, differences between expectations and the delivered product are likely to be lower, thus

FIGURE 2
Visual Perspective: Interactivity and Depth of Field

A: Interactivity



What you're wearing:

Women's Long Sleeve Royal Twill Shirt

Product Details

$44.00

What's my size?

Choose a color:

Items that go great with what you are wearing

Women's Solid No Iron Pinpoint Cotton Shirt

Women's 2x2 Rib Tank Top

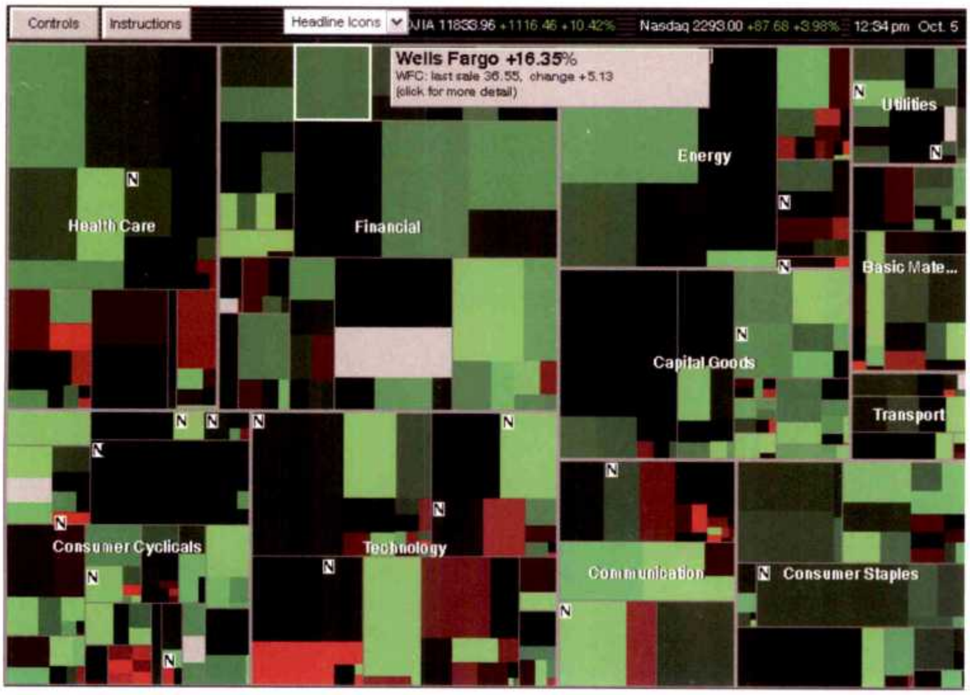
Women's Short Sleeve Supima Tee

Item 9 of 13 goes with:

© My Virtual Model Inc., 2004. Privacy policy Terms of service

Lands' End's My Virtual Model enables customers to create a model that looks like them and then virtually try on different outfits.

B: Depth of Field



DJIA 11833.96 +1116.46 +10.42% Nasdaq 2293.00 +87.68 +3.98% 12:34 pm Oct. 5

Wells Fargo +16.35%
WFC: last sale 36.55, change +5.13
(click for more detail)

SmartMoney.com's MarketMap provides both overview and detailed information about stock performance. Stocks are grouped by sector into rectangles whose size shows the firm's market capitalization and whose color shows performance. Green indicates that stock price is up (the brighter the green, the greater the gain), red indicates that stock price is down, and black means no change.

increasing postpurchase satisfaction (Ganapathy, Ranganathan, and Sankaranarayanan 2004; Oliver 1980). Finally, because interactive visualization tools, such as Nike's iD and Trek's Project One, allow consumers to see what different product configurations look like (e.g., whether a particular color combination on a bicycle will be attractive), consumers who use interactive visualizations are likely to make more heterogeneous choices than those who use text-based tools or photos of stock models.[1]

From a managerial standpoint, interactive virtual reality tools are likely to lead to better forecasts of demand, more accurate estimates of elasticity, and more profitable product displays because consumer behavior is more externally valid in virtual than in paper-based environments (Burke 1996; Burke et al. 1992). In particular, virtual reality tools can help managers understand how consumers will interact with a product. As with consumers, business buyers may be more likely to customize virtually presented products and require less product reworking.

This discussion leads to the following testable propositions:

P_1: Compared with noninteractive displays, interactive visualization tools lead to

  a. more information restructuring,
  b. information acquisition that more closely reflects the decision maker's preexisting preferences or knowledge structures,
  c. enhanced use of preexisting decision rules,
  d more compensatory decision processes, and
  e. more accurate decisions.

P_2: The use of interactive virtual reality visualization tools leads to

  a. higher prepurchase confidence,
  b. proportionally less physical than online search,
  c. greater product trial and adoption,
  d. smaller differences between actual and expected product performance,
  e. higher levels of postpurchase satisfaction,
  f. more heterogeneous choices,
  g. more accurate forecasts of demand and price elasticity when product testing occurs in virtual reality, and
  h. less postpurchase product reworking (returns and exchanges).

Depth of Field

Visual representations vary in depth of field—that is, the extent to which they provide contextual overview versus detail information or enable decision makers to keep both levels in focus at the same time. Depth of field is likely to affect how information is accessed and evaluated. For example, by converting a data point into a pencil-thin bar line, TableLens displays more data in a given space than traditional spreadsheets (Ganapathy, Ranganathan, and Sankaranarayanan 2004). For a manager assessing product sales across different retail stores, this may lead to a better understanding of the range of values of the visualized attributes. In addition, by locating more data in a given visual field, such tools lower the cognitive costs of adding alternatives to a consideration set (Hauser and Wernerfelt 1990); for a consumer, this is likely to increase the number of alternatives considered. At the same time, visualization tools that provide more context rather than more detail and tools that enable more alternatives to be displayed in a given visual field may lead to relatively less compensatory (more selective) decision processes as decision makers eliminate alternatives from consideration (Payne 1976).

Other tools allow decision makers to focus on specific data points. Spotfire's zooming scrollbars enable marketers to change the level of detail to see characteristics of a specific item sold in a specific store on a specific day or to see sales of a product and those of its competitors in multiple retailers over time. More detailed views with more information on each alternative tend to limit the number of alternatives considered, leading to more alternative-based (compensatory) processing (Payne 1976). Thus, a detailed view may lead a manager to focus on why sales were particularly high or low on a given day, whereas a context view may lead the manager to examine why sales have changed over time relative to competitive products. Changes in depth of field may also lead to overconfidence or underconfidence. In particular, visual representations that provide greater detail may lead to overconfidence as users make assessments on the basis of fewer observations, whereas visualizations that provide greater context may lead to underconfidence as users fail to adjust for the larger sample size (Griffin and Tversky 1992).

Other visualization tools emphasize context by showing the relationships between different pieces of information. For example, trees and networks (Card, Mackinlay, and Shneiderman 1999) can represent choice alternatives or illustrate a sales force structure, customers, and product sales. A disadvantage of trees is that they often become unwieldy with large amounts of data. Treemaps (Johnson and Schneiderman 1991) overcome this problem by representing hierarchies through subdivided rectangles so that the tree fits a smaller (rectangular) space; this provides decision makers with overview as well as detailed information (Plaisant et al. 2003), which is likely to increase understanding of attribute values and decision confidence. SmartMoney.com's MarketMap (Fidelity Investments 2006; see Figure 2, Panel B) enables investors to view market, industry, and individual stock performance simultaneously. By increasing the accessibility of contextual information, such tools may also increase decision makers' use of category relative to alternative-specific information. Consequently, consumers using MarketMap may be more likely to use industry and market performance in stock selection than those using traditional line graphs of price changes for a single stock. However, using tools such as Treemaps can be difficult for less experienced users (Bederson and Shneiderman 2003), suggesting that expertise is likely to moderate their relative advantages.

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[1] A counterargument might suggest a reverse effect. In particular, virtual reality visualizations may enable consumers to converge on the most attractive model, thus leading to more homogeneous than heterogeneous choices. Whether virtual reality leads to greater heterogeneity or homogeneity in choices is likely to depend on the extent to which consumers share ideal points (Carpenter and Nakamoto 1989) and to which the choice context encourages variety-seeking behavior (Ratner and Kahn 2002). We thank an anonymous reviewer for this suggestion.

Still other tools combine context with detail views. For example, when choice sets are represented through a hierarchical tree structure, alternatives that do not meet a decision maker's criteria can be "grayed out," whereas alternatives that are still under consideration remain colored. This allows the user to focus on a subset of alternatives but remain cognizant of others (Kumar, Plaisant, and Shneiderman 1997). Another approach is to prune (i.e., remove from display) leaves (e.g., specific alternatives) or branches (e.g., sets of alternatives) that do not meet particular criteria. Research suggests that though fully pruned trees are associated with faster decisions, satisfaction with the interface is highest for partially pruned trees—that is, tree structures that provide visual information about the aspects of eliminated alternatives (Kumar, Plaisant, and Shneiderman 1997). In general, this suggests that choice satisfaction and confidence are likely to be higher for decisions made using partially versus fully pruned structures. In addition, consideration sets tend to be larger when decision makers are instructed to exclude unfavorable alternatives than when they are instructed to include favorable alternatives (Levin, Huneke, and Jasper 2000; Levin, Jasper, and Forbes 1998), implying that more alternatives may be considered for visual representations that involve pruning rather than adding alternatives. For example, a consumer using a Web site with a tree structure of consumer electronics is likely to consider more alternatives than a consumer who must select specific alternatives to compare.

Other approaches to combining context and detail include using different windows to provide both overview and detailed views (Beard and Walker 1990); bifocal views, in which centrally located information is magnified and peripheral information is presented in a demagnified or billboard format (Robertson and Mackinlay 1993; Spence and Apperley 1982); and fish-eye views, which distort information such that focal information is larger and nonfocal information is smaller (Sarkar and Brown 1994). Some results show faster navigation and data identification when an overview is provided (Beard and Walker 1990), whereas others have found that though user satisfaction is higher, navigation may be slower because of the additional cognitive load of dealing with simultaneous views (Hornbæk, Bederson, and Plaisant 2002). Hornbæk and Frøkjær (2001) find that providing both overview and detailed views improves overall understanding of content, that detailed views alone lead to greater speed in answering specific questions, and that fish-eye views increase reading speed. This suggests that whether combining context and detail is superior to either one alone depends on whether the goal is to maximize accuracy or minimize effort (Payne, Bettman, and Johnson 1988). In particular, visual representations that provide contextual information should lead to more consistent preferences than those that do not. However, such representations are likely to involve greater decision-making effort and time.

This discussion leads to the following set of testable propositions:

P_3: Decision makers using visual representations that provide more context than detail or present more alternatives within a given visual field
  a. consider more alternatives,
  b. have a better understanding of the range of attribute values,
  c. engage in less compensatory processing,
  d. are less likely to exhibit overconfidence, and
  e. exhibit more consistent preferences.

P_4: Decision makers using visual representations that involve pruning alternatives from consideration rather than adding alternatives for consideration
  a. consider more alternatives and
  b. engage in less compensatory processing.

P_5: Decision makers using partially pruned rather than fully pruned and unpruned visual representations are more satisfied with their choices.

Information Context

Although the visual perspective affects the general relationship between visual information and the decision maker by changing the decision maker's ability to manipulate information and see both details and overview information, the information context affects *which* information the decision maker attends to. Changes in the particular data values, colors, and shapes used in a given visual representation affect how information is accessed and compared. We examine three aspects of information context. The first aspect is "vividness," or the salience of particular information. The second aspect is "evaluability," or the ease with which information can be compared. The third aspect is "framing," or how a given representation changes the reference point or scale against which information is evaluated.

Vividness

Vividness (Nisbett and Ross 1980) refers to the saliency or availability of specific information. More vivid visual information is likely to be acquired and processed before less vivid visual information (Jarvenpaa 1990). Visualization tools are likely to affect vividness simply by presenting data in a form that uses preattentive graphic features, such as line orientation, width, length, and color, which are readily processed with little effort (Bederson and Shneiderman 2003; Healey, Booth, and Enns 1995; Julesz 1981; Treisman 1985). The vividness of graphic information leads to greater attention and, together with interactivity, enhances telepresence, in which the experience of the virtual environment becomes more real than the immediate physical environment (Hoffman and Novak 1996; Steuer 1992).

The vividness of graphic information may increase its use in decision making (Glazer, Steckel, and Winer 1992; Jarvenpaa 1990). An increased focus on graphic information may come at the expense of ignoring other (relevant) information (Glazer, Steckel, and Winer 1992), lead to increased weighting of more salient attributes (Mandel and Johnson 2002), or lead users to overweigh less diagnostic information (MacGregor and Slovic 1986). For example, research in an advertising context has found that when the copy and pictures contain different information, the graphic information disproportionately influences inferences (Smith 1991). Similarly, risk perceptions are higher when relative risk is presented graphically and cost is presented in text format (i.e., numerically) than when both are presented in text format (Stone, Yates, and Parker 1997). Consequently, if consumers are shown a graph of relative product performance and text information on relative product reliability, they are more likely to assess the product on performance. This effect should be reversed if reliability is presented graphically.

In general, when visualizations include both textual and graphic information, the graphic information is likely to receive greater weight. Thus, visualizations using color to show day-to-day changes in stock prices or market share may lead decision makers to act on information that is simply random noise (Barber and Odean 2001, 2002; Gilovich, Vallone, and Tversky 1985). Similarly, providing airline passengers with maps of alternative routes rather than text-based city pairs may enhance Soman and Shi's (2003) finding that consumers prefer trips with only forward progress to those with backward progress but shorter trip times. In particular, map-based visual representations may lead users to focus on direction of travel rather than overall trip times.

Although, in general, graphic information may be more vivid than text information, certain types of visual representations are likely to be more vivid than others. In particular, shapes and colors that "pop out" from the background by being unique, by contrasting sharply, by having the greatest variation in size, or by having the greatest salience to human information processors (Benbasat and Dexter 1985; Jarvenpaa 1990; Simkin and Hastie 1987; Treisman 1988) will be more vivid and therefore more heavily used in decision making. For example, MacGregor and Slovic (1986) find that when facial characteristics are used to represent different features, greater weight is given to attributes represented by eyes and mouths, regardless of the predictive validity of the information represented by these more salient features. Similarly, by using color to make the direction of price changes more vivid, SmartMoney.com's MarketMap (Fidelity Investments 2006) may increase attention to this attribute. Other research suggests that in judgments of proportion, angles of 0 degrees, 90 degrees, and 180 degrees "jump-out" more than other angles (Simkin and Hastie 1987, p. 463). Therefore, if a manager is using a series of pie charts to evaluate salespeople in terms of meeting sales quotas, he or she will be more likely to attend to the performance of salespeople for whom these charts show right angles and to use their performance as a reference for evaluating their colleagues.

Even subtle changes in vividness can affect judgments and decision making. Cleveland and McGill (1984, 1985) find that changing the saturation level of colors in a two-color chart (from both high to both low) affects judgments of size of the two areas. In addition, less frequently occurring shapes and colors are more vivid and are more likely to receive attention because they provide more information and discrimination (West 1996). Furthermore, by focusing attention on particular observations, vividness tends to enhance attention to presented data relative to other information, such as information from memory. In general, decision makers may overestimate the relative frequency or probability of more vivid information (Sherman et al. 1985). For example, a pharmaceutical company using Spotfire's DecisionSite, showing sales by region, might overestimate demand for a drug when sales information is presented as frequency points on a map overlay because of the vividness of this information.

This suggests the following propositions regarding vividness:

P_6: Decision makers using graphic versus text-based presentations of the same information
- a. place greater weight on this information when it is presented graphically,
- b. are more likely to change their choices in response to changes in attributes, and
- c. are more likely to overestimate this information when making judgments.

P_7: Decision makers using visual representations that include graphic as well as text-based information
- a. place greater weight on the graphic information,
- b. are more likely to change their choices in response to changes in attribute values that are shown graphically, and
- c. overestimate the graphic information and underestimate the textual information.

P_8: Decision makers using visual representations for which some information shows greater variance in shape, size, or color
- a. place greater weight on information that shows more variance,
- b. are more likely to change their choices in response to changes in attribute values that show more variance, and
- c. overestimate high variance information and underestimate low variance information.

P_9: Decision makers using visual representations that vary in their presentation of features that are salient in human perception
- a. place greater weight on the more salient features,
- b. are more likely to change their choices in response to changes in attribute values that are shown by salient features, and
- c. overestimate information shown by salient features and underestimate information shown by nonsalient features.

Evaluability

Evaluability (Hsee 1996) refers to the ease with which information can be assessed and compared. By making it easier to compare information, visualization tools enable decision makers to notice changes, recognize outliers, and see patterns more quickly. Making information easier to compare is likely to lead to increased acquisition, weighting, and processing of this information (Ariely and Lynch 2000; Bettman and Kakkar 1977; Bettman and Zins 1979; Hsee 1996; Jarvenpaa 1989, 1990; Kleinmuntz and Schkade 1993; MacGregor and Slovic 1986; Russo 1977; Schkade and Kleinmuntz 1994).

Although practitioners often claim that information visualization leads to better, faster, and more confident decisions (Brath and Peters 2005), whether graphic or textual (tabular) presentations are superior likely depends on the fit between these alternative representations and the nature of the task (DeSanctis 1984; Vessey 1991). Tasks that are predominately spatial in nature include comparisons and assessments of trends, associations, and other relationships in the data. Primarily symbolic tasks include those that focus on discrete data values. Although the same information is presented, graphic presentations enhance the evaluability of spatial information, whereas tables (of numbers) enhance the evaluability of symbolic information (Vessey 1991). Graphic representations are likely to be superior for detecting trends, comparing patterns, and interpolating values. For example, a manager may be more likely to identify a competitor's product as a threat when viewing a visual representation that shows sales of his or her product and the competitor's product over time than when viewing the same information in a table. In contrast, tabular representations are superior for retrieving specific data values (Benbasat 1986; Benbasat and Dexter 1985; Jarvenpaa and Dickson 1988; Vessey 1991). Displays that combine both tabular and graphic information may lead to better performance than either graphic or tabular displays alone (Benbasat 1986).

Relative to tabular data, graphic presentations can lead to biased interpretations (Cleveland and McGill 1984, 1985; Krider, Raghubir, and Krishna 2001; Raghubir and Krishna 1996, 1999). Cleveland and McGill (1984, 1985) find that length judgments are more accurate than area judgments, which in turn are more accurate than volume judgments. Thus, in assessing differences between values, greater accuracy is expected when the information is presented in table form than when it is indicated by object size. Other research has found that the accuracy with which bar height is judged is lower for taller bars and when other bars are present (Zacks et al. 1998). This suggests that, in general, judgments of absolute values are less accurate for extreme values and when graphic information is provided on nontarget and target objects.

Among the most difficult graphs to interpret are those that require estimations of area. Figure 3, Panel A, shows an example of the familiar General Electric/McKinsey matrix used for business portfolio analysis, in which circles represent business units and the areas of the circles are proportional to market size. A similar approach is used to represent segment sizes on perceptual maps. The "size effect" (Teghtsoonian 1965) suggests that decision makers underestimate the magnitude of the difference between larger and smaller circles. This suggests caution when using area to illustrate relative quantities because such figures are likely to be misinterpreted.

Visual representations may enhance decision makers' ability to evaluate information on multiple attributes. In particular, visual representations support simultaneous processing and are likely to lead to more intuitive and holistic, rather than piecemeal, processing (Holbrook and Moore 1981; Sloman 1996). For example, an investor using TableLens to evaluate mutual funds (see Figure 3, Panel B) may develop more of a gestalt assessment of a mutual fund than an investor presented with the same data in text form. In addition, research on cognitive capacity shows that humans can process more information when it is presented graphically than when it is presented in text form (Miller 1956; Tegarden 1999). This suggests that in evaluating and choosing products, decision makers will use more attributes and engage in more compensatory decision processes when information is presented graphically. In addition, because interactions between features are more readily detected in graphic displays than in verbal descriptions, the relative strength of such interactions is likely to be stronger for graphic than for text information (Holbrook and Moore 1981). This also implies that decision makers who use visualization tools may be less able to explain their choices than those who use text-based tools, for which particularly desirable or undesirable aspects are more easily identified. Similarly, managers who use visualization tools may be less able to explain their decisions to top management than those who can point to specific (textual) data.

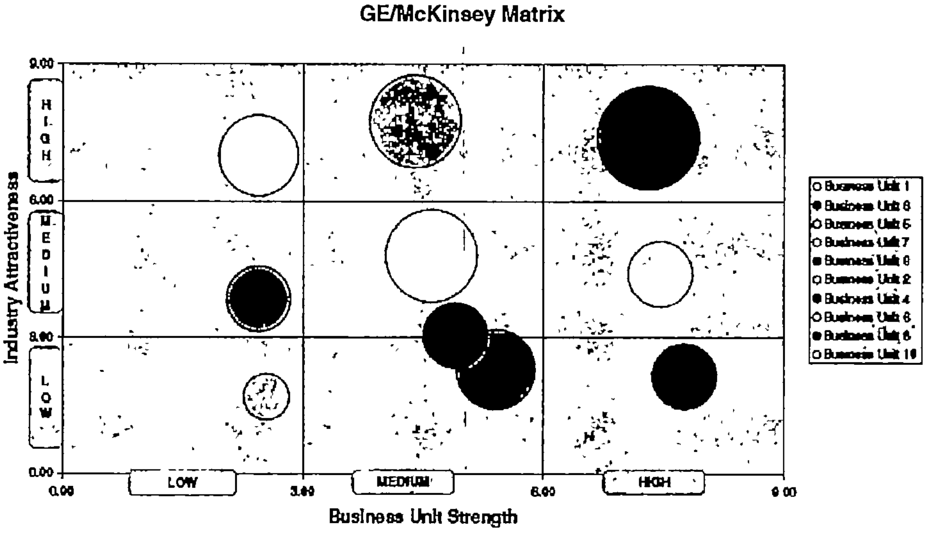
Differences in evaluability may also affect how decision makers acquire and evaluate visual information. Jarvenpaa (1989) finds that decision makers are more likely to acquire information by attribute when using bar charts organized by attributes but are more likely to acquire information by alternative when using bar charts organized by alternatives. Jarvenpaa (1989) also finds that information displays enhance by-attribute and by-alternative processing when the displays are congruent with attribute- or alternative-based choice rules. Similarly, Simkin and Hastie (1987) find that viewing bar charts leads to comparison judgments, whereas viewing pie charts leads to proportion judgments. In addition, alternative visual representations may affect the speed and accuracy of different decision processes. In Simkin and Hastie's studies, discrimination was faster and comparison judgments were more accurate when bar charts were used, whereas proportion judgments were more accurate when pie charts were used.

Similarly, the compatibility hypothesis (Slovic, Griffin, and Tversky 2002) suggests that information that is compatible with a given task will be given more weight. Thus, if a marketing manager's task is to rank-order salespeople and if a visual representation shows each salesperson's performance in dollar and unit sales and one of these is presented as a bar graph, which enables easy comparisons, and the other is presented as an area graph (circles), which makes comparisons more difficult, the manager is more likely to use the more compatible bar-graph information.

Finally, the evaluability of alternative visual representations is likely to affect the extent of compensatory versus noncompensatory decision making. Visualization tools that enable simultaneous viewing of multiple attributes can lead to more compensatory decision making than those that provide information on only a few attributes at a time (Jarvenpaa 1989). However, these effects may be tempered by the user's cognitive limitations and whether the visualization provides different visual cues and combinations of visual cues that can be holistically processed. For example, research using facial features to present financial information on multiple variables simultaneously to both skilled and naive users found that the schematic faces were processed more quickly with no loss in accuracy than when the same information was presented in financial ratios or accounting statements (Smith and Taffler 1996). Related research found that when predictive cues were represented

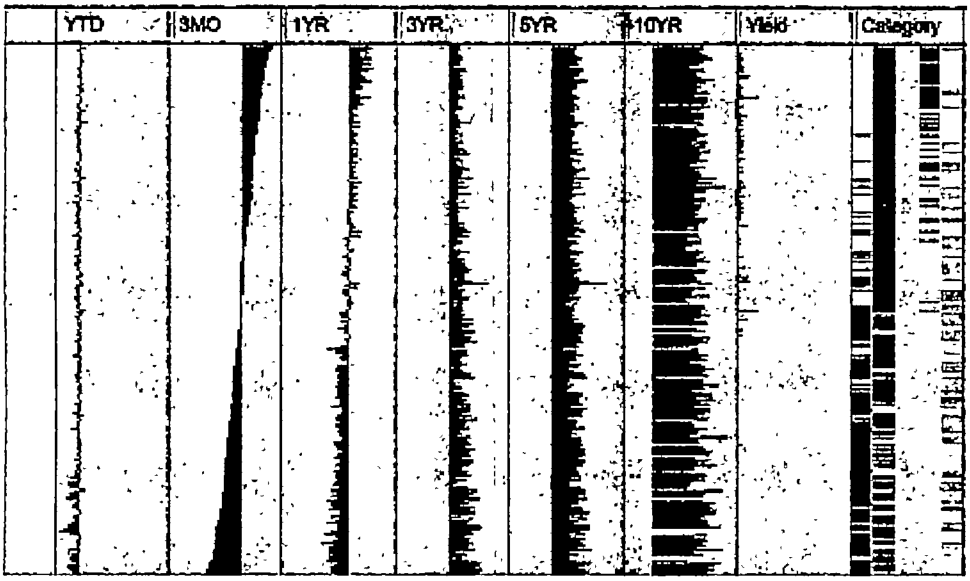
FIGURE 3
Information Context: Evaluability and Framing

A: Evaluability



In this example of the General Electric/McKinsey matrix, the circles represent business units, and the area of the circles is proportional market size. The size effect (Teghtsoonian 1965) suggests that decision makers will underestimate the magnitude of the differences between larger and smaller circles.

B: Framing



TableLens (Pirolli and Rao 1996; Rao and Card 1994) is a graphical spreadsheet that turns numerical data into columns of bar graphs that can be sorted and compared.

by different facial features, decision makers were more likely to use all the cues than when each cue was represented by the same visual features, such as bar graphs, deviation bar graphs, or spoke displays (MacGregor and Slovic 1986). These findings may have resulted from using a different facial feature (shape) for each cue or from decision makers' greater familiarity with making facial than symbolic assessments. This suggests two, though not necessarily conflicting, predictions: (1) Tools using different representations of cues (attributes) lead to more compensatory processing than tools using a single representation (shape) for each attribute, and (2) tools using familiar (to human) objects (e.g., faces, animals, houses) in which each cue is represented by a different feature (e.g., eyes and mouth, spots and tail length, house size and number of windows) lead to more compensatory processing than tools using different symbolic (nonmeaningful) shapes and colors for each attribute.

On the basis of this discussion of evaluability, we offer the following testable propositions:

P_{10}: Decision makers using graphic versus text-based (tabular) presentations of the same information

a. more quickly identify outliers, trends, and patterns of covariation between variables;

b. make less accurate assessments of differences between values;

c. use more attributes in judgment and choice; and

d. are less likely to attribute their judgments and choices to any single product feature.

P_{11}: Decision makers using visual representations that include graphic and tabular information show higher performance in terms of decision accuracy and speed than decision makers using either graphic or tabular formats alone.

P_{12}: Compared with decision makers who use visual representations that make it easy to compare alternatives on multiple attributes, decision makers who use visual representations that make it easier to compare alternatives on a particular attribute

a. place greater weight on that attribute,

b. are more likely to choose the alternative that is superior on that attribute, and

c are less likely to choose compromise alternatives.

P_{13}: Decision makers using visual representations that allow attributes (versus alternatives) to be more easily compared show greater processing by attributes than by alternatives.

P_{14}: Decision makers using visual representations that highlight the similarity among alternatives on a given attribute weigh other attributes more heavily in their decision making.

P_{15}: Decision makers using visual representations that are congruent with particular decision rules (processes) rather than visual representations that are incongruent with particular decision rules

a. are more likely to use those decision rules and

b. make faster and/or more accurate decisions.

P_{16}: Decision makers using visual representations with different visual representations of each cue (attribute) engage in more compensatory processing than those using visual representations with the same representation for all cues.

P_{17}: Decision makers using visual representations that represent different cues (attributes) using different aspects of objects that are familiar to human decision makers (e.g., facial features) engage in more compensatory processing than those using visual representations that use different aspects of unfamiliar objects.

Framing

By changing the presentation of a given problem, visual representations may accentuate biases and heuristics in decision making (Gilovich, Griffin, and Kahneman 2002; Hutchinson, Alba, and Einstein 2004; Kahneman, Slovic, and Tversky 1982). This could occur by changing the reference point against which data are compared, thus framing data alternatively as a loss or a gain. For example, SmartMoney.com's MarketMap (Fidelity Investments 2006) presents daily gains and losses. Because daily losses are more frequent and dramatic than losses over longer periods, a daily presentation is more likely to show losses than a longer-term presentation. Because decision makers are often risk seeking for losses but risk averse for gains (Kahneman and Tversky 1979), a visualization with a more recent reference point may lead investors to riskier behavior.

Visual representations may also aggravate biases by changing how decision makers process and evaluate information. Hutchinson, Alba, and Einstein (2004) find that compared with tabular and bar-graph presentations of the same data, line graphs lead to increased use of an "adjacent-differences heuristic," in which correlations are assessed by comparing differences on adjacent values of an independent variable with differences on adjacent values of the dependent variable. Hutchinson, Alba, and Einstein show that this bias can lead to greater spending on particular media in an advertising context or greater investments in a particular stock in a financial setting, even if both types of media (stock) are equally correlated with sales (financial returns). This suggests that compared with frequency-based representations (e.g., bar graphs, scatter plots), line-based representations increase biases such that decision makers infer greater levels of correlation between variables and make decisions that reflect this bias. Following Hutchinson, Alba, and Einstein's example, marketing managers who are given line-based representations of media spending versus sales are more likely to be biased in their interpretation of these data than those given the same information in bar-graph format.

Similarly, alternative visual representations may change the framing and, therefore, judgments about products. For example, Levin and Gaeth's (1988) finding that impressions of ground beef are higher when framed as 75% lean than when framed as 25% fat is likely to be replicated by visualizations that present a positive versus negative framing of the same information. Alternative visual representations may also moderate these framing effects. For example, if foods marked as green are perceived as healthful and foods marked as red are perceived as unhealthful (Synovate 2005), the perceived difference between nutritional pie charts that are 75% green and 25% red versus 25% green and 75% red may be greater than that between black-and-white versions of the same information.

Relatively subtle visual cues, such as the orientation of the object (e.g., whether a square is aligned with horizontal and vertical axes or rotated 45 degrees), can change which dimension is most heavily weighted in estimates of size and volume (Krider, Raghubir, and Krishna 2001). Likewise, by changing whether information is presented in absolute or relative terms, visual representations may change decision makers' preferences for integrating or segregating losses and gains (Heath, Chatterjee, and France 1995). In particular, visualization tools that make it easier to see changes in percentage terms (e.g., multiple pie charts) may lead to greater segregation of losses and gains than visualizations that facilitate absolute comparisons (e.g., line graphs). In general, visual representations are likely to change the anchors that decision makers use (Chapman and Johnson 2002; Tversky and Kahneman 1974). For example, a visual display of sales from highest to lowest may lead to higher overall sales estimates than a display from lowest to highest because of the tendency to place greater weight on initial information (Chapman and Johnson 2002; Tversky and Kahneman 1974). Figure 3, Panel B, shows a TableLens example that uses financial data in which eight dimensions (year-to-date, three-month, one-year, three-year, five-year, and ten-year performance; yield; and category) are displayed. Whether these columns are sorted from highest to lowest or vice versa is likely to affect investors' estimates of overall stock returns.

Finally, alternative visual representations may lead to context effects, such as violations of regularity (i.e., the attraction effect) in which the share of an alternative increases when alternatives that it dominates are added to a consideration set (Huber, Payne, and Puto 1982; Simonson 1989). Hamilton, Hong, and Chernev (2007) find that changing the perceptual organization of a choice set (e.g., by changing the display order of alternatives in a product-by-attribute matrix) can draw attention to unique attribute values in such a way as to moderate the strength of the attraction effect. This suggests that judgments and choices could vary depending on the order of alternatives in a visual representation. In particular, because order affects the ease with which alternatives can be compared on a given attribute, this may lead to an attraction effect for alternatives that are dominant on the easy-to-compare attribute. Because the attraction effect seems to depend on how readily alternatives can be compared on a given attribute (Hamilton, Hong, and Chernev 2007), it is more likely to occur with visual representations that display information by attribute than by alternative. Likewise, the compromise effect (Simonson 1989), in which the addition of a non-dominated alternative leads to increased choice of a compromise alternative, may depend on the extent to which a visualization enables easy comparisons of alternatives across attributes. If comparison is easiest for a single attribute, choice proportions are likely to increase for the alternative that is highest on that attribute; however, if comparisons on multiple attributes are easy, this should increase the choice of compromise alternatives. Thus, if a marketing manager is evaluating three new products on the basis of market share potential and profitability, his or her decision to go with a product that represents a compromise between these objectives may depend on whether the visual representation makes it easy to compare the products on both attributes simultaneously.

This suggests the following set of testable propositions regarding framing effects:

P_{18}. Decision makers using visual representations that present data with a more recent reference point engage in more risky decision making than those using visual representations that present data with a less recent reference point.

P_{19}: Decision makers using visual representations that present data in a continuous fashion rather than in frequencies are more biased in their interpretations, such that

a. perceived correlations between variables are higher and

b. their allocation decisions reflect comparisons among adjacent levels of variables.

P_{20}: Decision makers using visual representations are influenced by the vividness of information, such that visual saliency moderates the effect of positive versus negative frames on judgments.

P_{21}: Decision makers using visual representations that present changes in percentage terms (e.g., pie charts) are more likely to segregate gains and losses (mixed gains) than those using visual representations that make it easier to see absolute changes (e.g., line graphs).

P_{22}: Decision makers using visual representations that sort information from highest to lowest make higher estimates than those using visual representations that sort information from lowest to highest.

P_{23}: Decision makers using visual representations that make information easier to compare on an attribute for which one alternative is dominant are more likely to make decisions that are consistent with the attraction effect than those using visual representations that make comparisons on that attribute more difficult.

P_{24}: Decision makers using visual representations that display information by attribute are more likely to make decisions that are consistent with the attraction effect than those using visual representations that display information by alternative.

General Discussion

Summary

Recent advances in information technology have led to expanding capabilities to collect, store, and disseminate data, and there is no sign of this trend abating. However, this explosion of data is a mixed blessing. Although more data can lead to more informed decisions, they can also be overwhelming. To help decision makers cope with the increasing amount of data, an expanding array of visualization tools is available. Although the developers and sellers of these tools promise better, faster, and deeper insights from the use of their product, there has been little investigation into when and how visualization tools affect decision making.

This article draws on theoretical and empirical results in various fields to identify key aspects of visual representations that are likely to affect the visual decoding process. Specifically, we focus on (1) the visual perspective, which includes interactivity and depth of field, and (2) the information context, which includes vividness, evaluability, and framing. These two aspects are not intended to be comprehensive but rather to highlight factors that are common to many situations and tools and to stimulate further research. We draw on theory and prior research findings to posit how these two aspects of visual representation affect decision making.

Potential Moderators

The propositions in this article are largely those of main effects, in which a particular characteristic of visual representation (e.g., interactivity) is posited to affect a particular type of decision-making behavior (e.g., restructuring). However, several proposed effects are likely to be contingent on factors such as expertise, involvement, and need for touch (see Figure 1). We offer some examples of how these factors are likely to moderate the effects of visual representation on decision making.

Expertise is likely to be a moderator for several of our propositions. In particular, how much visual representations change decision-making processes likely depends on users' knowledge of which factors are important and their ability and motivation to change the visual representation to reflect these factors. For example, P_1 proposes that interactive displays lead to more information restructuring, enhanced use of preexisting decision rules, and more compensatory decision making. At the same time, there is evidence that (novice) decision makers tend to use information as it is presented (Bettman and Kakkar 1977; Slovic 1972) and that they often do not know which features are relevant for product evaluations (Sujan 1985). Thus, when novice decision makers are presented with a particular visualization, they may assume that the variables represented are the most relevant and that the default visualization is best. This means that novice users may fail to take advantage of interactivity and will tend to use the default visualization, regardless of its appropriateness for a given task. For example, consumers may be less likely to recognize improvements in reliability for a particular automotive brand if the default view is a scatter plot rather than a sorted table visualization, such as TableLens, because scatter-plot views can make trends more difficult to see (Kobsa 2001).

Other propositions likely to be moderated by expertise include P_6–P_9, for which vivid information is more likely to be overweighted by novices than by experts (who are less likely to use vividness to infer attribute importance), and P_{18}, for which changing reference points is likely to have a greater effect on the riskiness of decisions made by novices than those made by experts, who may be less subject to such visual framing effects. In general, propositions that claim a superiority for visual versus text-based representations, such as P_6, are likely to depend on decision-maker expertise.

Similarly, involvement may play a moderating role because many visualization tools require user effort. Using interactive visual representations to restructure information and explore different options (P_1 and P_2) requires the decision maker to (1) identify which aspects are important and (2) interact with the visualization to display these aspects. Likewise, using visualizations that involve selecting or eliminating alternatives (e.g., P_4) requires the decision maker to play an active role. Unless the decision is sufficiently important, the user may be unwilling to engage in the cognitive and physical effort needed to realize the full benefits.

Need for touch (Peck and Childers 2003) may also be a moderator, particularly for P_2, which suggests that virtual reality representations substitute for real-world information search. However, the direction of this effect is difficult to predict. People who are high in need for touch may believe that there are more benefits to virtual reality because it mimics their preferred search environment. At the same time, people who are high in need for touch may believe that there are fewer benefits because most of these representations do not provide the tactile feedback they seek.

In addition to the decision maker's characteristics, such as expertise, involvement, and need for touch, data characteristics may serve as moderators. These include the number of data points, the extent to which there are lagged effects in the data, and the correlations among attributes. In particular, the proposed effects of P_{10}, in which graphic data enable faster identification of trends but less accurate assessments of differences, are likely to be greater for smaller data sets. For example, Krider and colleagues (2005) find that visual analysis outperforms traditional econometric analysis for inferring causality in data sets with relatively few observations. Similarly, lagged effects may be more accurately identified using visual representations than textual displays or statistical analysis (Diehl and Sterman 1995; Krider et al. 2005). Further research could explore situations in which visual representations may outperform traditional statistical approaches. Finally, the implications of P_{19}, in which perceived correlations between variables are greater for visualizations that present data in a continuous fashion, are likely to depend on whether correlations actually exist in the data. To the extent that such correlations exist in the data, visual representations may be helpful; however, visual representations may also lead decision makers to infer correlations when there are none.

Managerial Implications

As business systems produce ever-increasing amounts of data, the challenge to extract the most value from this growing flood of information increases as well. Visualization tools have the potential to offer managers and consumers ways to improve efficiencies, reduce costs, gain new insights, make data more accessible, and increase satisfaction. At the same time, visualization tools may accentuate biases in decision making. We summarize key implications —both positive and negative—of visual representations.

Efficiencies, cost reductions, and improved productivity. Many visualization tools speed up routine analysis tasks by making it easier to see correlations, outliers, and trends and to make comparisons. By reducing the time required for analysis, firms may require fewer staff or, alternatively, do more with current staffing. A manager for a large European mobile phone retailer estimated that visual representation reduced his time spent analyzing sales data by 20%, freeing time to spend on other tasks (Borzo 2004). Similarly, Smith and Taffler (1996, p. 82) conclude that "by providing a speedy, accurate method of processing information," visual representation of financial information may free up valuable management time. Sales managers, assistant brand or product managers, media buyers, and others who routinely analyze large amounts of data could benefit from increased productivity that visualization tools can offer.

New insights. In addition to improved efficiencies for routine tasks, visualization tools may enable users to uncover new insights that would otherwise have gone unnoticed. Youngworth (1998) reports that a consumer goods manufacturer saved hundreds of thousands of dollars in shipping costs by using visualization software that made exceptions "stand out." Lucent Technologies uses visual representation software to help identify new business opportunities (Borzo 2004). Similarly, visualization tools might help marketing managers uncover formerly undetected patterns that are useful for cross-selling or up-selling. At the same time, because such tools that make exceptions stand out, they may lead marketers to focus too much on outliers rather than data that represent the core of their business.

An area with high potential for using visualization tools for data exploration and ad hoc discovery is clickstream data (Eick 2000). Traditional Web server log tracking and reporting often generate lengthy reports that are ineffective for identifying the trends, outliers, patterns, and connections needed to understand critical questions, such as which vehicles drive the most traffic to a Web site, how visitors navigate the site, and patterns that lead to abandoned shopping carts (Eick 2000). Another area is the use of visualization tools to uncover trends in textual data, such as that found in product blogs and discussion groups. For example, Tilebars (Hearst 1995) could be used to provide a visual representation of text string occurrences in a text file through bar graphs that show the relative length of a document coupled with embedded squares that show the frequency and location of specific terms.

Increased information accessibility and decision confidence. Applications such as MarketMap and CreditMap (Fidelity Investments 2006; Panopticon 2003), which make voluminous stock and corporate bond market information more accessible to customers, can lead to greater customer satisfaction and can potentially enhance loyalty and retention. By creating an interactive and more realistic portrayal of alternatives with dynamic imaging and the ability to customize, virtual reality applications have the potential to be a win–win choice for consumers and firms. Online retail sites, including Lands' End, Timberland, and La-Z-Boy, have used virtual reality to increase sales and retain customers (Esfahani 2005).

However, it is also possible that complex visualization tools that require significant learning to master fully may confuse, frustrate, and discourage novice users. For example, MarketMap is a Treemap, a type of tool that novices often have difficulty using (Bederson and Shneiderman 2003). Managers should ensure that users have the ability and motivation to learn how to use such tools before providing them to decision makers.

Potential biases. Although visual representations may enable more data to be processed than a textual presentation, they may also enhance biases in decision making. An awareness of these biases is important for those who use and design visualization tools to aid decision making. For example, visual representations that provide detailed views of alternatives may lead decision makers to make incorrect evaluations by considering only a portion of the data. In addition, the vividness of visual information may lead marketing managers to place inordinate weight on such information, regardless of its diagnosticity. Similarly, by increasing the evaluability of particular attributes, visual representations may lead decision makers to focus on attributes that are easiest to compare rather than those that are most important. Because humans have difficulty comparing graphic portrayals of area and volume, visual representations that use such graphic techniques may lead decision makers to inaccurate assessments. For example, the familiar General Electric/McKinsey matrix uses area to portray market size; this will likely lead to inaccurate perceptions of the actual size differences among markets. People who prepare such visual representations for decision makers should not assume that they will be correctly understood. Likewise, visual representations can lead to biased estimates of correlations and subsequent decisions that reflect this bias (Hutchinson, Alba, and Einstein 2004). In general, even seemingly innocuous decisions about color choice, orientation of shapes, and selection of markers can influence users' judgments and decisions.

Because visual representations draw on the associative rather than the rule-based reasoning system (Sloman 1996), their use may be best suited for situations in which hunches and intuition often lead to the same results as more systematic analysis. When such intuitive approaches are likely to lead to incorrect conclusions (e.g., because of biases in interpretation), traditional data formats may better serve marketing managers. Another approach is to encourage the use of visualization tools for exploration but to subject insights from visual representations to formal analysis.

Because consumers are likely to use the vividness and evaluability of attributes in a visualization to infer importance and are less likely to be able or motivated to change visual representations, default visualizations should be selected with care. This is particularly true when the intent is to aid consumer decision making (e.g., in choosing nutritious foods or a health care plan that meets people's specific needs). If determining a default representation is problematic (e.g., because consumers vary in their preferences), it may be preferable to build visual representations on the fly on the basis of questions that elicit preferences.

Conclusions

When a visual representation is created, information is encoded by aspects such as color, texture, and geometry. When the decision maker sees the representation, these aspects are decoded. The representation "works" only if the visual decoding is accurate and efficient (Cleveland and McGill 1984, 1985). Two ways to further the understanding of this decoding process are to (1) draw on theoretical and empirical findings in relevant areas, such as visual perception, and (2) conduct empirical studies—in particular, controlled experiments—to explore effects or test specific hypotheses.

This article offers a set of theoretically based propositions that are suitable for rigorous empirical investigation. However, current empirical support for our propositions is largely anecdotal. A key next step is empirical research to further the understanding of the posited effects of various visualization tools for decision making. Further research is needed to test these propositions in both controlled and field settings across different types of tasks. One avenue for additional work is to explore potential moderating variables. In particular, studies involving decision makers who vary on key individual difference attributes, such as level of expertise or need for touch, would further the understanding of the implications of visual representations for decision making. Another avenue for research is to examine how decision makers use graphic and textual information together. In particular, many visual representations enable users to see detailed textual information on the individual data points that make up the visualization. For example, SmartMoney.com's MarketMap (Fidelity Investments 2006) allows users to click on individual stocks to reveal earnings, financial ratios, and other text-based information and, in this way, engages decision makers in deliberative and associative information processing. Thus, visual representations offer an interesting setting for examining two systems of reasoning (Sloman 1996) and the potentially sequential, parallel, and interactive nature of these processes. There is no doubt that visual representations will become more prevalent, and we hope that the framework and propositions presented in this article will stimulate further research.

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Americus Reed II, Karl Aquino, & Eric Levy

Moral Identity and Judgments of Charitable Behaviors

In several studies, the authors examine the potential to leverage a consumer's moral identity to enhance brand and company identification and promote goodwill through community relations. Studies 1a and 1b show that even when opportunity costs are equivalent (subjectively or economically), consumers who also have a highly self-important moral identity perceive the act of giving time versus money as more moral and self-expressive. The authors extend these findings to self-reported preferences and establish boundary conditions in two additional studies. Consumers with higher organizational status prefer to give money versus time, but this preference is weaker for those with a highly self-important moral identity (Study 2), and the preference for giving time versus money is more likely to emerge when the moral self is primed and the time given has a moral purpose (Study 3).

Individual and corporate financial donations in the United States amount to more than $241 billion per year (see the American Association of Fundraising Counsel's Web site at http://www.aafrc.org). The volunteering of time generates services valued at more than $272 billion annually. Approximately 40,000 organizations are able to exist because of consumers who are willing to give time as an inexpensive and free labor source (Fisher and Ackerman 1998; Independent Sector 1992; Kotler 1982). Indeed, some consumer needs can be met only when time is given by others, such as volunteers who provide companionship, inspiration, and emotional support at organizations such as Big Brothers/Big Sisters (e.g., Clary et al. 1998). Marketing's long history of concern with social welfare through consumer exchange (Bagozzi 1974, 1975; Gundlach and Murphy 1993) and corporate social responsibility (Drumwright 1999; Handelman and Arnold 1999; Klein, Smith, and John 2004; Lichtenstein, Drumwright, and Braig 2004; Robin and Reidenbach 1987) makes consumer perceptions of and preferences for qualitatively different types of donation behavior important research issues.

Although charities are faced with a consistent need for services, shrinking government support and competition make it more challenging to encourage donation (Bendapudi, Singh, and Bendapudi 1996). The question of how nonprofit organizations should request help and what type of help to request is critical. Along these lines, Rothschild (1979, p. 11) notes the incongruities of nonprofits that try to "sell brotherhood like soap." Although some research in marketing has examined charitable promotion strategy (Bendapudi, Singh, and Bendapudi 1996), little empirical research has explored the solicitation of time versus money (cf. Reed, Aquino, and Levy 2007). Brand equity benefits may accrue to organizations that encourage the donation of time. A corporation that mobilizes its employees to donate company time (rather than money) may be perceived as being more community centric, expending more effort, and being a better corporate citizen. Identifying social-psychological factors that might motivate consumers to volunteer time could have considerable practical value.

The intended contribution of this article can be divided into two parts: (1) We test core ideas about an understudied psychological construct (i.e., moral identity) and judgments of charitable behaviors, and (2) we extend the implications of these ideas to self-reported preferences for such behaviors (giving time versus money). We present an overview of the empirical work in Figure 1.

We explore whether moral identity is related to judgments of and self-reported preferences for giving time versus money. In each study, we use different ways to equate the two resources to hold their "value" constant. In Study 1a, we ask participants about their perceptions of giving time versus money after having them place a subjective dollar value on their time. Study 1a shows that consumers who have a highly self-important moral identity are more likely to perceive giving time (versus money) as a relatively moral act (i.e., caring, moral, socially responsible, and heartfelt). People with a highly self-important moral identity also find the act of giving time versus money to be relatively more self-expressive. Study 1b shows that these kinds of perceptions extend to hypothetical corporations. The contribution of these two studies is that they examine judgments about equivalent charitable behaviors as a function of a potentially important internal factor. Although these core ideas have not been previously tested in both marketing and social psychology, they are not surprising. However, they are the foundation for the main empirical contribution of this arti-

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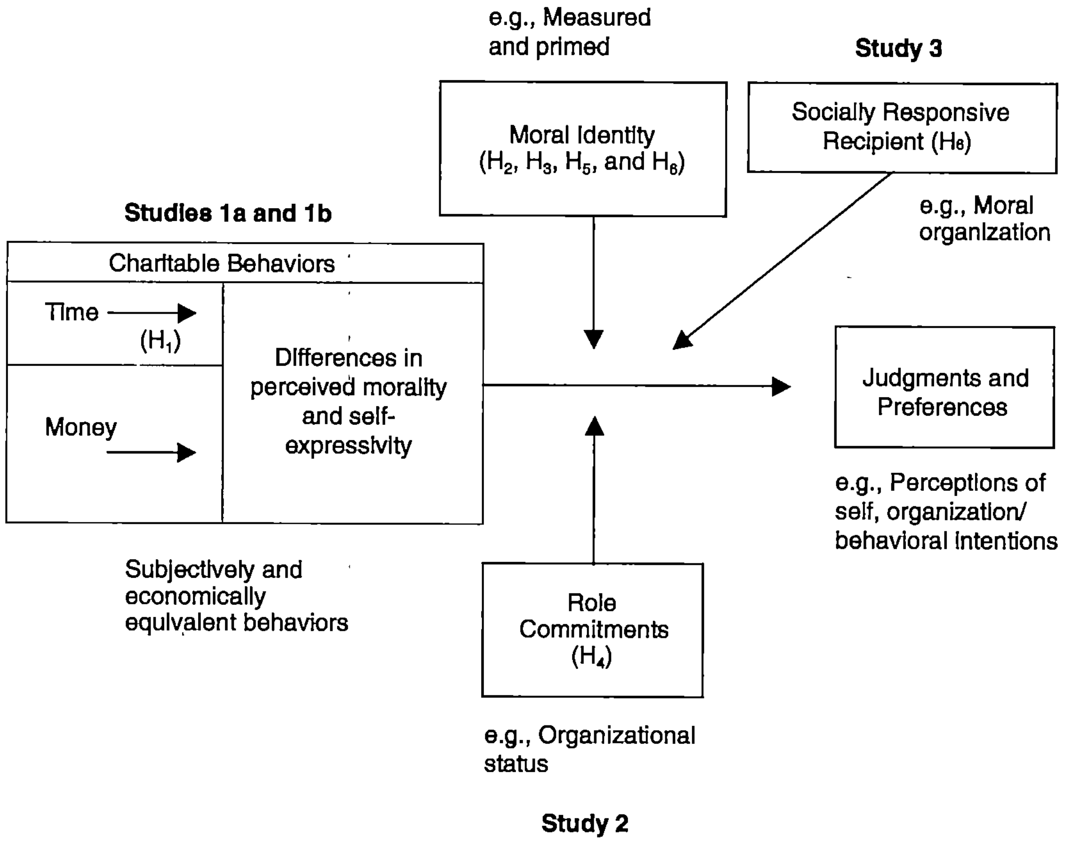
FIGURE 1
Overview of Empirical Work


e.g., Measured and primed
Study 3
Moral Identity (H_2, H_3, H_5, and H_6)
Socially Responsive Recipient (H_6)
Studies 1a and 1b
e.g., Moral organization
Charitable Behaviors
Time (H_1)
Money
Differences in perceived morality and self-expressivity
Judgments and Preferences
e.g., Perceptions of self, organization/ behavioral intentions
Subjectively and economically equivalent behaviors
Role Commitments (H_4)
e.g., Organizational status
Study 2

cle. Study 2 is a field study of working adults that tests whether consumers are more likely to prefer giving time to donating money when their moral identity has high self-importance and when career commitments are less demanding. In this study, time is equated to each participant's opportunity cost associated with his or her monetary wage rate. Finally, Study 3 is a laboratory study that establishes causality by showing that people whose moral identities are primed are more likely to prefer giving time than money, and this preference is even stronger when the organization is one that assists others in need. In Study 3, we present participants with a choice and allow them to place whatever dollar value they want on the amount of time given. Studies 2 and 3 extend social identity research by testing relationships among the self-importance of moral identity, preferences for charitable giving (time versus money), and the boundary conditions of these relationships.

Conceptual Framework

Giving Time Versus Money

Researchers define "moral behavior" as behavior that is socially responsive to the needs of others (Gilligan 1982; Kohlberg 1969; Rest 1979). Thus, a consumer who donates time and one who gives money both engage in moral behavior. However, some economic theories would predict consumer indifference between making a monetary donation to a cause and giving time to that cause if the two resources are equivalent in "value." For example, if a person believes that his or her time is "worth" $50 per hour and is asked to choose between donating $200 to a charitable organization and spending four hours of time to assist that charity, he or she should be indifferent between these choices, all else being equal. However, recent behavioral decision theory has suggested that effort directed toward some stimulus (e.g., task, goal, good) is psychologically different from spending the same amount of money (Kruger et al. 2004; Morales 2005; Thaler 1981).

Researchers have demonstrated that a common attribution (assuming that no other information is salient to undermine this inference) is that effort implies confidence in a cause/product (Kirmani 1990; Kirmani and Wright 1989), especially under conditions of indeterminable or ambiguous product quality (Kruger et al. 2004). When products or services appear similar, the cue of greater firm effort may lead to more favorable consumer perceptions (Kirmani 1990; Kirmani and Wright 1989). Another important distinction is the difference between doing and paying. Whereas exerting effort often leads to different inferences about motivation (Bandura and Cervone 1986) and/or internal value (Kirmani 1990), giving money does not necessarily trigger similar inferences. In some cases, giving money leads to negative attributions (Morales 2005; Webley and Wilson 1989). For example, a consumer may view corporate tax-efficient giving as cold and detached. Furthermore, Morales's (2005) work shows that exerting effort indicates that a consumer cares more about the activity or cause. These ideas set the stage for testing some key ideas in this article. A purpose of Study 1a and Study 1b was to conduct a simple test to examine people's perceptions of giving time versus money when the value of the two resources are equivalent:

> H_1: When the value of the two resources is held constant, consumers will perceive giving time (giving money) to an organization that provides a social good as a moral (less moral) act.

These arguments are consistent with Morales's (2005) and others' (e.g., Kruger et al. 2004) findings about the utility derived from effort in situations in which the giving of time and money is perceived as equivalent in value. However, we build on their work by examining internal psychological factors (i.e., a consumer's moral identity) that might influence perceptions of and preferences for giving time versus money.

The Definition of a Consumer's Moral Identity

Aquino and Reed (2002) propose that people possess a cognitive schema of the moral self that is organized around a set of moral trait associations. Aquino and Reed's trait-based definition of moral identity builds on the work of other writers (e.g., Brewer and Gardner 1996); they argue that traits are the loci of self-definition around which personal identities are structured. We adopt this definition of moral identity as a mental representation (i.e., a self-image) that a consumer *may* hold about his or her moral character (see Aquino and Reed 2002). For example, a consumer may possess in his or her mind a typical exemplar of what a moral person is like in terms of characteristics (e.g., being kind, honest, and loving), feelings (e.g., showing concern or empathy for others), and behaviors (e.g., helping strangers, engaging in charitable behaviors). A consumer's moral identity (the extent to which this image is an important part of his or her self-concept) may motivate choices and the pursuit of actions that demonstrate social responsiveness to the needs of others.

This connection between how a person views him- or herself and the connection to his or her preferences for different kinds of behavior is an orientation that many psychologists and moral philosophers consider critical to the definition of morality. For example, Damon and Hart (1992, p. 455, emphasis added) argue that "there are both theoretical and empirical reasons to believe that the *centrality* of morality to self may be the single most powerful determiner of concordance between moral judgment and conduct.... People whose self-concept is organized around their moral beliefs are highly likely to translate those beliefs into action consistently throughout their lives." For some consumers, moral identity is both the antecedent and the outcome of the need for self-consistency between who a person thinks he or she is and how he or she acts in the world (Blasi 1993).

However, consumers have multiple identities (Markus and Kunda 1986), and some identities are more important than others to the self. We expect that moral identity is more likely to regulate judgments (e.g., perceptions of charitable behaviors) when it is relatively more top of mind (i.e., temporarily salient) and/or when it is relatively more important to a consumer's self-concept (i.e., self-important).

The Self-Importance of Moral Identity as a Moderator of Judgments of Giving Time Versus Money

Social identity can influence a person's judgments, choices, behavior, and performance when it becomes salient, self-important (i.e., strength of identification), and relevant to the decision (e.g., Reed 2004). Moreover, identity-based judgments tend to be resistant to change (Bolton and Reed 2004). Salient and self-important identities trigger consumers to process information and engage in behaviors that they believe to be consistent with that identity (Forehand, Deshpandé, and Reed 2002). For example, advertisements targeted at different racial groups make consumers who are members of these groups pay more attention, especially if their racial identity is made salient (Forehand, Deshpandé, and Reed 2002). Building on this research, we propose that when a consumer's moral identity (Aquino and Reed 2002) is highly salient or self-important, his or her sensitivity to acts that are consistent with moral identity increases.

Because giving time more directly involves the self, a consumer with a relatively highly self-important moral identity should make a different inference about giving time versus money. Consumers with a relatively highly self-important moral identity should react differentially toward charitable acts, even if the acts are equivalent in value. The self-importance of moral identity should directly influence a consumer's perceptions of giving time versus donating money such that giving time will trigger a stronger moral inference. We test this possibility in the following hypothesis:

> H_2: When the value of the two resources is held constant, consumers will perceive giving time (giving money) to an organization that provides a social good as a moral (less moral) act. This effect will be stronger for consumers who have a relatively highly self-important moral identity.

The rationale for this hypothesis is as follows: To the extent that moral identity takes on high importance within a consumer's overall self-definition, acts that are more expressive of the goals, values, and attitudes implied in this identity (e.g., giving time) should be evaluated differently from those that are comparatively less self-expressive (e.g., giving money). Conversely, if moral identity holds little or no importance in a consumer's overall self-definition, he or she should be largely insensitive to expressing preferences for different kinds of moral behaviors that are equivalent in value. As a result, the notion that giving time represents a greater investment of self than donating money should matter little to a consumer with a relatively less self-important moral identity because these two acts may be viewed as qualitatively similar.

Because the giver and beneficiary need never, and often do not, interact, consumers with a relatively highly self-important moral identity should perceive monetary donations as impersonal, indirect, and passive and, thus, a less moral way of providing a social benefit to others. However, giving time more intimately connects the giver to the receiver. At the very least, giving time connects the giver to others who provide the social good directly. Therefore, giving time constitutes a greater psychic and behavioral investment of the self than giving money, especially for those with a highly self-important moral identity.

Finally, consumers who have a highly self-important moral identity should report stronger psychological affiliation toward acts that reinforce their moral self-concepts (i.e., acts that are consistent with their moral identity and are self-expressive of their morality). If the arguments presented thus far are valid—that is, a consumer with a highly self-important moral identity perceives giving time versus money as a more moral act—it follows that consumers whose moral identity has high (versus low) self-importance should also believe that giving time is a relatively more self-expressive act, even when the two acts are equivalent in value. The following hypothesis tests this idea:

> H_3: When the value of the two resources is held constant, consumers with a relatively more self-important moral identity will perceive the act of giving time (versus money) as relatively more self-expressive.

The rationale for this hypothesis is rooted in the attitude function literature. Prior work has argued that people hold and report an attitude because the attitude serves a "social adjustment function" (Smith, Bruner, and White 1956, p. 42). In other words, the attitude enables the person to connect and identify with others who also share that same attitude. This connection also results in a stronger sense of identification (i.e., psychological affiliation and liking) with behaviors that reflect the particular social identity (Shavitt 1990). Across the first three studies, we used Aquino and Reed's (2002) empirically validated measure of the chronic self-importance of moral identity to examine whether this facet of the self predicts judgments of and preferences for charitable behaviors that are equivalent in value.

Study 1a: Perceptions of Equivalent Charitable Behaviors

Method

Sample and procedures. Study 1a tested the influence of the self-importance of consumers' moral identity (measured as a covariate) on their perceptions of equivalent charitable behaviors. The convenience sample consisted of 242 undergraduate students, administrative staff, and local area community residents who participated in a one-hour session in which they were compensated for completing several research tasks. Of those who reported demographics, 39% were men, 46% were Caucasian, 7% were African American, 39% were Asian, 3% were Hispanic, and 5% self-reported as "other"; the average age was 22.31 years (SD = 7.16).

The study was cross-sectional and consisted of several ostensibly unrelated tasks. For the first task, participants completed a short prequestionnaire on general self-perceptions and opinions. Embedded in this questionnaire were items that measured participants' self-importance of their moral identity (we describe this subsequently).

Participants then completed a study on their perceptions of charitable giving. After participants read the scenario and answered the questions to the best of their ability (there were no right or wrong answers), they were prompted with the following:

> 1. How much free leisure time do you usually have per week? Please write an hour amount: _____.
> 2. How much money is this free time worth to you? In other words, how much would you be willing to pay to keep this free time? Please write a dollar amount: _____.
> 3. Now consider these two acts of donation:
>   - Giving your leisure to helping out at the Charity of your choice the number of hours that you wrote in response to Question 1.
>   - Giving an equivalent amount of money to the Charity of your choice in the amount of money that you wrote in response to Question 2.
>
> Now, assume that the Charity of your choice that hypothetically receives either of these two gifts has NO preference toward which "type of help" they receive.
>
> In other words, the amount of time donated OR the money donated is an amount such that the Charity of your choice is able to more than cover gross wage expenses, benefits, and transaction costs for hiring for its staffing needs.

After reading this scenario, participants responded to several items that assessed their perceptions of the self-expressiveness of giving money (the number they wrote down) and giving time (again, the number they wrote down). Participants then responded to questions that measured the moral inferences made about giving time versus money. Finally, we asked participants whether they thought about the costs (noted in the scenario) born by the charitable organization when they were answering the question.

Measures. Drawing on Erikson's (1964) definition of an identity as being rooted in the very core of a person's being and involving being true to the self in action, Aquino and Reed (2002) propose that two dimensions tap into the self-importance of moral identity. The first dimension reflects the degree to which moral traits are deeply rooted in the self-concept (internalization), and the second reflects the degree to which these moral traits manifest publicly through the person's actions in the world (symbolization). We used Aquino and Reed's ten-item measure to assess the self-importance of moral identity (for the items, see the Appendix). Respondents answered the ten questions on Likert-type items (1 = "strongly disagree," and 7 = "strongly agree"). The measure consists of two subscales that tap into the internalization and symbolization dimensions of moral identity. We averaged the items for each subscale. The Cronbach's alpha reliabilities for internalization and symbolization were .79 and .76, with means of 6.28 (SD = .62) and 4.43 (SD = .95), respectively.

We measured the extent to which giving money is perceived as self-expressive by prompting participants with the following: "Hypothetically speaking, giving money in the amount you wrote down would...." We measured the following response items on a seven-point Likert scale (1 = "strongly disagree," and 7 = "strongly agree"): "be my voluntary choice," "reflect the type of person that I am," "represent the kind of activity I often think about," "be an important priority for me," "represent 'who I am,'" and "be a natural thing for me to do." A Varimax-rotated factor analysis showed that these items loaded onto one dimension, so we collapsed the items into an aggregate measure ($\alpha = .90$) in which higher numbers represented higher levels of self-expression.

Participants responded to the following prompt: "Hypothetically speaking, giving time in the amount you wrote down would...." We asked the same questions as we did for the previously discussed measure to assess the self-expressivity of the act of giving time. Again, we collapsed these measures into an aggregate score ($\alpha = .93$) on the basis of a Varimax-rotated factor analysis that showed that these items loaded onto one dimension. Because we were interested in self-expressive differences across money versus time, we used the same items to measure both and to tease them apart.

We asked participants to indicate which of the two acts was more "caring," "moral," "socially responsible," and "heartfelt" by responding on a seven-point scale (1 = "giving money," and 7 = "giving time"). We averaged these four items to form a scale ($\alpha = .72$) in which higher numbers indicated that participants perceived the act as being more moral.

We controlled for variables that were not of direct interest in the study but that might be related to attributions and perceptions of the charitable behaviors. We controlled for gender because it has been suggested that women are more oriented toward an ethic of care than men (Gilligan 1982). As a result, they may be more likely to infer stronger moral inferences in giving time. This variable was dummy coded (0 = male, and 1 = female). We controlled for age because polling data indicate that older people are more likely to be civic minded and to volunteer for community services (Putnam 2000); thus, age might influence consumers' perceptions of giving time. We also controlled for religious participation because there is some evidence that people who attend religious services are more likely to give time to community service activities than those who do not attend (Myers 2000). Consequently, religious participation (e.g., Williams and Lawler 2001) might influence inferences about giving time versus money independently of the self-importance of moral identity. We measured this variable by asking respondents to indicate how frequently they attended a place of worship during the past year using the following response format: regularly, occasionally, only on special days (Christmas, Yom Kippur, Ramadam), and not at all. These response categories were coded 4, 3, 2, and 1, respectively, so that the higher number indicated more frequent religious participation. Finally, 16% of the sample indicated that they had some idea about or thought of the charitable organization's costs when making their judgments of the two charitable behaviors. Thus, we controlled for this by creating a dummy-coded variable (0 = had no idea of/did not think about recipient's costs, and 1 = had some idea of/thought about recipient's cost).

Results

The test of H_1 is a t-test on the perceived morality variable. Note that participants provided their unique subjective value of their time such that the act of giving time was equivalent to giving money to the hypothetical charity of their choice. Although the two acts were equivalent in value, participants nonetheless believed that giving time was more caring, moral, socially responsible, and heartfelt ($t = 21.90$, $p < .05$) than giving money, consistent with prior research. The more important analysis was whether this difference would be explained by the self-importance of consumers' moral identity (H_2) and whether the two acts would be differentially self-expressive as a function of moral identity. We used hierarchical regression to test H_2 and H_3. We regressed the perceived morality variable, the self-expressivity of time variable, and the self-expressivity of money variable onto the controls in Step 1. We added the internalization and symbolization subscales of moral identity in Step 2. This analysis enabled us to test the incremental variance explained by the self-importance of moral identity. Consistent with H_2, we found a significant effect of internalization ($\beta = .38$, $t = 3.58$, $p < .05$) on moral inferences, such that participants who were higher on the internalized dimension of the self-importance of moral identity reported that giving time (versus money), though objectively equivalent in dollar value, was more caring, moral, socially responsible, and heartfelt. We also found support for H_3. Participants who were high internalizers ($\beta = .47$, $t = 2.78$, $p < .05$) and who were high symbolizers ($\beta = .49$, $t = 4.19$, $p < .05$) reported stronger perceptions of giving time as being self-expressive. Although we found a significant effect of symbolization ($\beta = .39$, $t = 3.24$, $p < .05$) on participants' self-expressivity of giving money, consistent with H_3, the set of internalization and symbolization variables explained twice the variance in their self-expressivity of giving time ($R^2 = .17$, $F = 6.94$, $p < .05$) compared with their self-expressivity of giving money ($R^2 = .09$, $F = 5.57$, $p < .05$).

Study 1b: The Self-Importance of Moral Identity and Perceptions of Equivalent Corporate Actions

Method

Sample and procedures. We conducted a second study to determine whether the kind of effects found in Study 1a (moral inferences) would also emerge when people judge corporations that give time versus money. The convenience sample consisted of 58 undergraduate students, administrative staff, and local community residents who participated in a one-hour session in which they were compensated $10 for completing several research tasks. Of those who reported demographics, 35 were men, 23 were Caucasian, 8 were African American, 21 were Asian, 2 were Hispanic, and 3 self-reported as "other"; their average age was 21.14 years (SD = 6.54).

The study consisted of several parts. In the first part, participants completed Aquino and Reed's (2002) ten-item measure of self-importance of moral identity as part of a "self-attitudes" questionnaire. There were then several unrelated filler tasks. In the main task, participants completed a "scenario" study in which they were asked to give their impressions of two hypothetical organizations that participate in charitable activities.

Similar to Study 1a, participants were presented with the following instructions, which preceded descriptions of two hypothetical organizations:

> Corporation A and Corporation B each sponsor (separate) philanthropic programs in which they donate to a community outreach organization that provides free job training to unemployed workers in the local region. Though the opportunity cost (bottom-line financial cost) to each company is the same, each decides to donate in a different way.
>
> - Corporation A, which had net profits of 20 million dollars last year, organized a program whereby it donates .5% of its net profits to the outreach organization. Thus, multiplying the net profit amount by the percentage earmarked for the outreach organization, the company donated $100,000 in cash last year. This money was spent helping to provide job training to the unemployed workers.
> - Corporation B, which also had net profits of 20 million dollars last year, organized a program whereby its employees volunteered a combined 5000 hours (during working time) to the outreach organization last year. At an average employee salary of $20 an hour, Corporation B donated $100,000 in employee working hours. This time was spent helping to provide job training to the unemployed workers.

After reading these two descriptions, participants answered several questions about the two hypothetical corporations. They then completed the remaining tasks for the experimental session, were debriefed, were paid for their time, and were dismissed.

Measures. As in Study 1a, we administered Aquino and Reed's (2002) ten-item measure before the corporation scenario to assess the self-importance of moral identity (see the Appendix). Respondents answered the ten questions on Likert-type scales (1 = "strongly disagree," and 7 = "strongly agree"). We averaged the items for each subscale. The Cronbach's alpha reliabilities for the internalization and symbolization scales were .86 and .85, with means of 6.34 (SD = .745) and 4.26 (SD = 1.18), respectively.

Participants responded to the following seven questions about the two corporations: "Which company is more caring?" "Which company is a better corporate citizen?" "Which company shows greater concern for the welfare of others?" "Which company is more socially responsible?" "Which company is more involved with its community?" "Which company is more moral?" and "Which company displays a greater social conscience?" Participants then checked one of six boxes with Corporation A at one end of the scale and Corporation B at the other end of the scale. We coded these measures such that higher scores indicated that Corporation B was viewed as possessing more favorable reactions with respect to the items we measured. A Varimax-rotated factor analysis showed that these items loaded on one dimension. We averaged them to form a scale ($\alpha = .93$).

As an additional, nonmoral proxy of the extent to which people value and protect their time, we wrote seven questions to measure participants' perceptions of their own time. Participants responded to the following statements on a seven-point Likert scale (1 = "strongly disagree," and 7 = strongly agree"): "I always use my time to 'get things done'"; "Only lazy people spend their time doing nonproductive things"; "I do not squander away my time"; "It is quite OK to spend your time doing 'nothing'" (reverse coded); "Time is my most important resource"; "In general, I would say I'm the type of person who values my time"; and "Time is one of the most important resources that I personally have." A Varimax-rotated factor analysis showed that these items loaded onto a single dimension. We averaged them to form a scale ($\alpha = .84$). We used the same control variables in Study 1a as in Study 2b.

Results

As in Study 1a, we tested whether the self-importance of moral identity predicts the likelihood that participants would view the hypothetical organization that gave time as being more caring, socially responsible, moral, and so forth. We regressed the dependent variable onto gender, age, and religious participation in Step 1. In Step 2, we entered internalization, symbolization, and people's own perceptions of the value of their time into the model. There was a significant effect in the regression for the internalization variable ($\beta = .41$, $p < .05$), indicating that higher scores on the internalization measure were positively correlated with higher perceptions of Corporation B (the time-giving corporation) as being more caring, being a better corporate citizen, showing greater concern for the welfare of others, being more socially responsible, being more involved with its community, being more moral, and having a greater social conscience. Symbolization and the value of time had no impact. Neither did any of the control variables.

Discussion and Limitations of Studies 1a and 1b

Study 1b showed similar results to those we found in Study 1a. We showed that the self-importance of moral identity (as measured by the internalization dimension) is related not only to self-reinforcing attributions made about the subjectively equivalent act of giving time versus money but also to inferences drawn about the moral activities of corporations. We also showed that this inference is not due to people's general perception that their time is highly valuable; the measure of people's general motivation to "protect" their time had no impact in the analysis. In addition, we explicitly told participants that the financial costs to the two organizations were identical, moving toward resolving the issue as to whether the participants intuitively understand value as defined by economic opportunity costs. Notably, as in Study 1a, the symbolization dimension in Study 1b did not affect participants' perceptions of which corporation was relatively more caring.

Although Studies 1a and 1b provide preliminary evidence for the theoretical arguments outlined in this article, several limitations still apply. The data suggest that consumers whose self-conception is relatively more organized around a set of moral traits will infer stronger perceived morality regarding the behavior of both individuals and corporations and will psychologically identify (i.e., perceive the behavior as more self-expressive). However, this does not necessarily mean that the self-importance of moral identity will be related to consumers' actual preferences for donating time versus money. An important extension of the implications of the perceptions of giving time versus money is to examine the influence of a consumer's self-important moral identity on preferences and behavioral intentions to engage in the two acts and to examine boundary conditions of these preferences.

Moreover, Studies 1a and 1b were both lab studies and, to some extent, are unable to tap into the complexities of real-life decision making. For example, we stated previously that an important issue in the marketing of organizational brand identity is how to encourage employees to give of themselves through voluntary acts that strengthen ties between their companies and the community. Although this goal is socially laudable, it presents a conundrum for many consumers because they occupy multiple social roles in life (e.g., parent, employee, Protestant, civic leader), each having a unique set of expectations and time commitments. It is likely that from time to time, the role expectations and corresponding self-identities attached to various consumer social positions conflict. Even when direct conflict among role expectations is absent, consumers must decide how to allocate personal resources of effort and money. If such an issue were examined in a more complex field setting, the results could provide additional evidence regarding the external validity of the arguments in this article and also could establish a preliminary boundary condition on the impact of moral identity's self-importance on preferences for charitable behaviors.

Study 2: Effects of the Self-Importance of Moral Identity on Preferences for Charitable Behaviors

In a recent article drawing on Jackall's (1988) study of moral behavior in organizations, Weaver and Agle (2002) suggest that the more numerous and important consumers' work-related commitments based on their organizational role, the stronger is their organizational identity relative to other identities. In contrast, people with less important and fewer commitments based on their organizational role will be less likely to act on organizational role expectations when such expectations conflict with role expectations and norms based on their other identities. On the basis of this reasoning, Weaver and Agle conclude that though people at the top of an organizational hierarchy have greater freedom to define organizational role expectations and, therefore, greater freedom to be guided by certain identities (e.g., religious identity), consumers with higher organizational status paradoxically have less psychological capacity to act on these values than people in the organizational periphery, who have fewer and/or weaker organization-based commitments.

If this thesis is valid, it is reasonable to suggest that consumers at the top of the organization, who are more likely to have a stronger organizational identity, will be more psychologically committed to achieving organizational or career goals than to pursuing civic or community-based goals that may be consistent with their other identities. This argument is consistent with Frederick's (1995) observation that values of economizing and power aggrandizing often found in business organizations can dominate an employee's personal values. Furthermore, as consumers rise through the organization and receive higher salaries, the value of their time increases, and it becomes less "rational" to spend it on anything other than making money (Linder 1970). Finally, it may be that as a person's psychic energy becomes invested in achieving material or career success, his or her sensitivity to other rewards, such as helping others, begins to atrophy (Csikszentmihalyi 1999).

These conditions present powerful psychological barriers against volunteerism among high-status organizational members and make the donation of money more attractive. First, unlike writing a check, volunteerism takes time, and time tends to be a scare resource for busy, ambitious people who make a lot of money and who have multiple organizational commitments. Second, if people who advance to the highest levels of the organization get there by devoting most of their energy to their careers, it is conceivable that their sensitivity to rewards that might be gained from voluntary service may atrophy, as Csikszentmihalyi (1999) suggests. Finally, even when high-ranking people have leisure time that they might reasonably devote to community service, their organizational identities may be so overpowering that they devote that time to career-related goals, such as playing golf with people even higher up in the organization, attending industry conferences, or socializing with important clients. As a result, they cannot devote time to civic goals, such as volunteering at the local soup kitchen or being a Boy Scout leader. Thus, we propose that the consumers who are most likely to prefer donating money to offering voluntary services when opportunity costs are held constant are those who occupy high-level positions in organizations. The following hypothesis tests this prediction:

> H_4: When the value of the two resources is held constant, the higher an employee's organizational status, the more likely he or she is to prefer giving money to volunteering time to an organization that renders a social good.

However, as we mentioned previously, because consumers possess multiple identities, it is conceivable that if a person's moral identity has sufficiently high self-importance, it may neutralize or even dominate the organizational role identity of high-status employees. If so, not only will moral identity have a direct effect on the preference of working adults to volunteer rather than to donate money to organizations that provide a social good, but the self-importance of moral identity might also mitigate the effect of organizational status that H_4 predicts. Accordingly, we propose that having high organizational status will not lead employees to prefer giving money to volunteering time if their moral identity has high rather than low self-importance; this is an important implication of differential preferences for giving time versus money that were established in testing core ideas about the self-importance of moral identity and judgments of giving time versus money. The following hypothesis tests this prediction:

> H_5: When the value of the two resources is held constant, moral identity moderates the relationship between organizational status and the preference for giving money rather than volunteering, such that the relationship is weaker for people whose moral identity has high rather than low self-importance.

Method

Sample and procedure. The convenience sample consisted of adult community residents located throughout the United States. The community residents were all alumni of the College of Business and Economics at a mid-Atlantic university. The college's alumni office provided a list of names and contact information for 927 alumni. Mail surveys were sent to people on the list who reported a U.S. address. The measure of self-importance of moral identity was part of a more comprehensive survey assessment that included several other measures that were not of direct interest in the current research. The survey included a cover letter that explained that the purpose of the study was to assess people's beliefs about engaging in certain activities. The letter informed respondents that all answers to the survey would remain anonymous and confidential. Three hundred sixty-one participants returned their surveys. We analyzed only the responses of 310 alumni who reported working full time because they were the most likely to experience the conflict between moral identity and career commitments. The remaining respondents reported working either part time (n = 27) or not at all (n = 24). Of the full-time employees who reported demographics, 73% were women, and nearly all (96%) were Caucasian. Their average age was 41 years (SD = 9.6), and they averaged 19 years (SD = 10.0) of work experience. Of the respondents, 30% reported working in executive-level positions, 17% were upper-level managers, 27% were mid-level managers, 4% were first-level supervisors, and 21% were nonmanagerial employees. Of the 310 full-time alumni, 274 provided usable data on all study variables, for a 30% response rate.

Establishing a context. We presented the choice of giving time versus money to a community service organization to participants by initially asking them a series of questions that provided a context in which we could assess their preferences. First, they estimated and wrote down how much "free time" they had during an average week with which they could "realistically" spend volunteering for some kind of community service activity. Second, they estimated and wrote down their hourly salary and multiplied this number by the amount of free time they reported in the first question. This step was designed to make the opportunity costs of giving time in monetary units salient. Finally, they chose which of three options they would prefer: (1) to give the free time they wrote in the first question to their favorite community service organization, (2) to write that organization a check for the amount of money they calculated after multiplying the amount of free time they had by their hourly salary, or (3) neither. Participants were told that they could choose only one option. The choice scenario used in Study 2 accounts for each participant's strict economic opportunity costs and time availability. Thus, there was considerably greater variability in the opportunity costs of giving time in Study 2, though the relative value of time versus money was still held constant for each respondent.

Measures. We measured the construct of giving time versus money by the respondent's self-reported preference to volunteer time, donate money, or do neither. We used Aquino and Reed's (2002) ten-item measure to assess the self-importance of moral identity. Cronbach's alpha reliabilities for the internalization and symbolization subscales were .70 and .8, respectively (see the Appendix). We measured the organizational status variable by asking respondents to report their job level using the following categories coded 1–5, respectively: nonmanagerial, first-level supervisor, midlevel manager, upper-level manager, and executive-level manager. For reasons we described in the previous studies, we also controlled for gender (0 = male, and 1 = female), age, and religious participation. In addition, we controlled for impression management by including items from Paulhus's (1991) measure of this construct ($\alpha = .80$).

Results

We used multinomial logistic regression to test the study hypotheses because the choice options were nonordered and binary. We treated giving money as the reference category in the regression; thus, the relevant contrasts are between service and giving money and between doing neither (not donating) and giving money. We centered the two dimensions of the self-importance of moral identity and the organizational status variable before creating the interaction term to minimize multicollinearity between the interactions and their individual components (Aiken and West 1991). The likelihood ratio test revealed significant effects for impression management ($\chi^2 = 7.85, p < .05$), symbolization ($\chi^2 = 14.79, p < .01$), organizational status ($\chi^2 = 9.66, p < .01$), and the internalization × status interaction ($\chi^2 = 6.63, p < .05$). The parameter estimates for the choice contrasts (service versus money and neither versus money) showed that people who scored higher in impression management were less likely to choose neither than money ($\beta = -1.21, p < .01$). The symbolization dimension had a significant effect on the likelihood of choosing service over money ($\beta = .61, p < .05$) and a marginally significant, negative effect on choosing neither over money ($\beta = -.66, p < .10$). These results are consistent with the theoretical argument in this article that the self-importance of moral identity affects consumers' preferences for giving time over money, even when the two resources are equal in value.

We predicted that consumers with high organizational status would prefer giving money to giving time, and indeed the negative parameter estimate for the organizational status variable on the likelihood of choosing service over money supports this prediction ($\beta = -.38$, $p < .01$). For every one level that employees advance in the organizational hierarchy (i.e., from nonmanagerial, to first-level supervisor, to midlevel manager, to upper-level manager, and finally to executive-level manager) the odds of preferring giving time versus money when opportunity costs are constant decrease by 29%, in support of our predictions. However, the main effect of organizational status is qualified by the significant internalization × organizational status interaction we reported previously.

We theorized that the self-importance of moral identity would moderate the effect of organizational status such that the preference for giving money rather than volunteering would be weaker for consumers whose moral identity has high self-importance than for those whose moral identity has low self-importance. The significant parameter estimates for the internalization × organizational status interaction on the contrast between service and money provide initial support for this prediction ($\beta = .63$, $p < .05$). We also found a significant interaction effect on the contrast between neither and money ($\beta = 1.01$, $p < .05$).

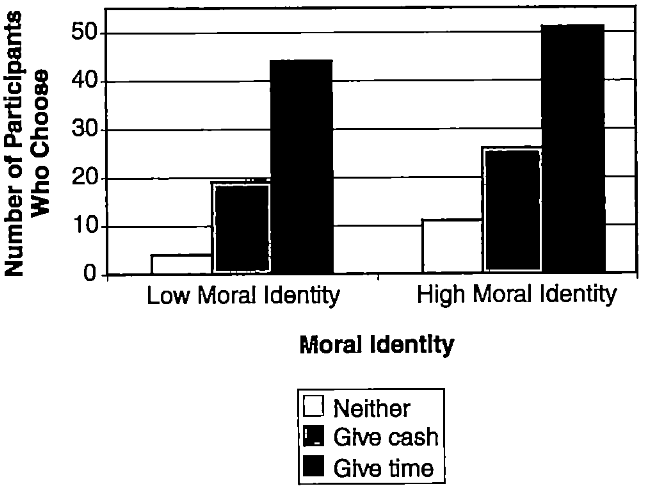
We analyzed the form of these interactions by performing a multinomial regression on organizational status within groups that scored high versus low on the internalization measure. We determined group assignment by a median split on this measure. The results showed that organizational status was significant for low ($\chi^2 = 9.38$, $p < .01$) but not for high ($\chi^2 = 2.63$, not significant) moral identifiers. The parameter estimates for the choice contrasts in the low-moral-identity group showed that people with higher organizational status were less likely to choose service over giving money ($\beta = -.47$, $p < .01$) and were marginally less likely to choose neither over money ($\beta = -.47$, $p < .06$). To depict this pattern of results, Figure 2 graphs the number of participants who chose to give time, money, or neither as a function of organizational status and moral identity (i.e., their internalization scores). These results are consistent with our predictions because consumers whose moral identity had high self-importance did not show a significantly greater preference for giving money over time as their organizational status increased.

Discussion and Limitations of Study 2

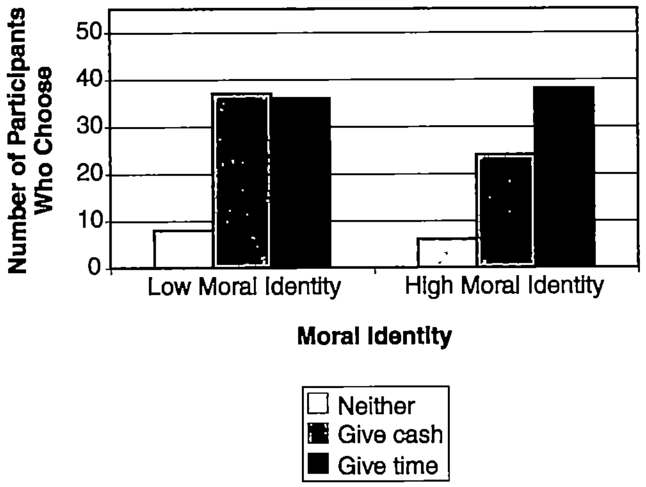
Study 2 suggests that the self-importance of moral identity is a promising construct for explaining preferences to give time versus money; an interpretation of this finding is that having a highly self-important moral identity may act as a countervailing force to the organizational commitments associated with a high-status position. A critical limitation of our conclusions is that the self-importance of moral identity may not play a causal role. Although prior research has painstakingly tried to validate the psychometric properties of the measure we use in these studies (e.g., Aquino and Reed 2002; Reed and Aquino 2003; Reed et al. 2006), as with any research whose focal independent variables are individual difference measures, it is entirely possible that the self-importance of moral identity is correlated with other, unobserved causal variables that produce the effect regarding perceptions of and preferences for the giving of time versus money. Study 2 attempted to rule this out by examining a logically consistent moderating variable (organizational status); however, perhaps the most compelling way to "rule in" the causal role of the self-importance of moral identity would be an orthogonal experiment in which moral identity is manipulated. For example, participants' moral identities could be primed, and then participants could be asked whether they would prefer to donate time or money in various situations. Similar to Studies 1a, 1b, and 2, we predict that people with a highly salient moral identity will be more likely to donate time, particularly when that time is being given to an organization whose main goal is to assist in the needs of others (i.e., a moral goal). We

FIGURE 2
Study 2: Joint Effect of Organizational Status and Moral Identity on Choices to Give Time, Money, or Neither

A: Low Organizational Status



B: High Organizational Status



Notes: Graphs are based on a median split of the internalization dimension of moral identity.

conducted Study 3 to address these three limitations and to test the following hypothesis:

> H_6: When the value of the two resources is held constant, participants whose moral identity is primed are more likely to prefer giving time than giving money. This effect is more likely to occur when the time is being donated on behalf of a moral purpose.

Study 3: Priming Moral Identity and Assessing Preferences for Giving Time Versus Money

The purpose of Study 3 was to provide a causal test of the effect of moral identity on preferences for giving time versus money. Thus, we made moral identity either more or less salient and observed whether this affected self-reported preferences to give time or money to a charitable or noncharitable organization.

Method

Sample and procedures. The convenience sample consisted of 179 undergraduate students, administrative staff, and local area community residents who participated in a one-hour session in which they were compensated for completing several research tasks. Of those who reported demographics, 79 were men, 44% were Caucasian, 13% were African American, 31% were Asian, 6% were Hispanic, and 6% self-reported as "other"; their average age was 22 years (SD = 5.82).

The study consisted of four parts. For Task 1, participants completed a short prequestionnaire about people's perceptions of their "busy-ness." Task 2 was a general-opinion survey in which we measured their impression management tendencies. Task 3 was a "handwriting" study, and Task 4 was a "donation request" study. After completing these four tasks, participants were paid $10 for their time; they were thanked, debriefed, and dismissed. We describe each of these tasks in more detail next.

Measures. We attempted to prime participants' moral identities in the third handwriting task presented in the lab session. Participants were told that "the purpose of the exercise is to examine people's handwriting styles as they tell stories." Participants were given a 9 × 5 matrix that contained nine words listed in each row in the first column. The participants were asked to write down (in their own handwriting) the nine words across the remaining four columns such that each participant wrote down the nine words four separate times. On the next page, participants were told to "take a few moments to think about each of these words. In the box below, write a brief story about yourself (in one or two paragraphs) which uses each of these words at least once. It may help you if you visualize each word as it is relevant to your life." Participants then completed manipulation checks and other unrelated questions that served to bolster the handwriting cover story. Participants were randomly assigned to one of two conditions. In the low-moral-prime condition, the nine words were "book," "car," "chair," "computer," "desk," "pen," "street," "table," and "trash can." In the high-moral-prime condition, the nine words were the salient induction stimuli in Aquino and Reed's (2002) instrument: "caring," "compassionate," "fair," "friendly," "generous," "helpful," "hardworking," "honest," and "kind" (see the Appendix).

Immediately following the handwriting task, participants completed the donation-request study. They were told that for a future study, the lab had been contacted by organizations to assess people's perceptions of and desire to volunteer different kinds of resources to help fundraising efforts. Participants were asked to imagine that they would come to the lab and be faced with the following hypothetical choices:

- You can donate $_____. (Imagine that after this session you would simply give to an organization some of the cash you will be compensated for participating in today's session.)
- You can donate $_____ worth of your time. (Imagine that after this session you would be taken to another classroom where you would spend time stuffing envelopes on behalf of the organization.)
- You can choose to do neither. (Imagine that after this session you would simply be compensated and you would then be free to leave.)

Participants were told to "please keep in mind that there is no right or wrong answer." They were told that they should not feel obligated to donate money or time to the particular effort. They were also told that "for this data to be useful, it's important that you simply report your true preferences. For example, choosing the third option is perfectly acceptable." They were then told to choose one of the aforementioned options. We coded their reported choices as follows: 1 = do not give, 2 = give cash, and 3 = give time.

On the next page, participants then responded to open-ended questions that asked them to briefly describe their reasons for the hypothetical choices that they made on the prior page. Finally, participants were asked questions to assess their perceptions of the organization for which they decided to not give, to give money, or to give time.

For the hypothetical donation study, participants were randomly assigned to one of two conditions that manipulated the kind of organization they were considering for their hypothetical choices. In the low-moral-organization condition, the organization was the American Marketing Association. Before making their choice, they were told that any provision of resources (money or time) would assist the American Marketing Association in its ongoing efforts to produce high-quality marketing resources for marketing professionals. In the high-moral-organization condition, the organization was the American Red Cross. Before participants made their choice, they were told that any provision of resources (money or time) would assist the American Red Cross in its ongoing efforts to respond to the needs of others who require aid and assistance.

As a replicate, we also manipulated the amount of money that would be given to the organization. In the low-resource condition, participants made the choice of not donating, giving $3 cash to the organization, or giving $3 worth of their time to the organization. In the high-resource condition, participants made the choice of not donating, giving $5 cash to the organization, or giving $5 worth of their time to the organization. We did this because participants were being asked hypothetically to consider choosing to donate a portion of the \$10 they would receive after completion of the research tasks. Participants were randomly assigned to one of these two conditions.

As in our previous studies, we measured gender, age, and religious participation as control variables with the same coding scheme as in Study 2. In Task 1 of the study, we collected measures of and controlled for people's general value of their time by asking them the same seven items from Study 1b. The Cronbach's alpha for this variable was .72. In Task 2 of the study, we collected Paulhus's (1991) impression management measure to attempt to control for socially desirable responding ($\alpha = .79$). Higher numbers on this variable reflect a stronger propensity to respond with a socially desirable answer.

Results

To check on the moral-prime condition, we asked participants some cover story questions about the stories they wrote in the handwriting task. We asked them about the extent to which the story they wrote reflected how they view themselves as (1) a student, (2) a member of an organization, (3) a moral person, and (4) safety conscious. We submitted each of these items to an analysis that contained the main effect of the moral-prime condition and the control variables. This analysis showed that participants in the high-moral-prime condition reported that their stories significantly reflected how they view themselves as a moral person to a greater extent than those in the low-moral-prime condition (Moral-prime $\text{condition}_{\text{LOW}} = 2.67$, Moral-prime $\text{condition}_{\text{HIGH}} = 5.12$; $F(1, 159) = 77.30$, $p < .05$). We also found an effect of impression management such that participants who scored higher on socially desirable responding also reported that their stories were relatively more reflective of them being moral. No other effects were significant.

We included two questions to ensure that participants believed that if they hypothetically decided to give money or time to the American Red Cross, their efforts would be perceived as going toward an organization with a moral purpose. At the end of the donation study, we asked participants, "In this specific example, (giving money or time to ______), to what extent did you think that giving time or money would be going to a moral cause?" and "In this specific example, (giving money or time to ______), to what extent did you think that giving time or money would help others in need?" Respondents answered the two questions on Likert-type items (1 = "strongly disagree," and 7 = "strongly agree"). We averaged these two questions to form a reliable scale ($\alpha = .91$). We submitted this analysis to a model that contained the control variables, the main effects and all possible higher-order interactions of the moral-prime manipulation, the moral-organization manipulation, and the amount-of-resources manipulation. The only significant effect was a main effect of the moral-organization manipulation ($F(1, 153) = 161.33$, $p < .05$), such that participants in the American Red Cross condition believed that their resources would be going to a moral organization that assisted in helping others who were in need (Moral-organization $\text{condition}_{\text{LOW}} = 2.23$, Moral-organization $\text{condition}_{\text{HIGH}} = 5.22$).

We submitted the control variables and the main effects and all possible higher-order interactions of the moral-prime condition, the moral-organization condition, and the amount-of-resources condition as predictor variables of the choice not to donate (1), to give cash (2), or to give time (3). As in Study 1a, we used multinomial regression because these three options are nonordered categorical responses. The overall maximum likelihood ratio test revealed significant effects for gender ($\chi^2 = 10.63$, $p < .05$), the moral-organization manipulation ($\chi^2 = 67.69$, $p < .05$), and the moral-identity prime × moral-organization two-way interaction ($\chi^2 = 7.17$, $p < .05$).

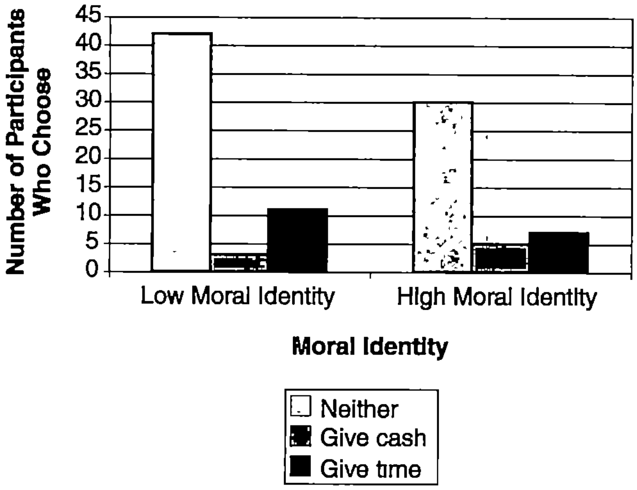
We then examined the parameter estimates for the three exhaustive binary contrasts of the dependent measure. Overall, men were 4.2 times more likely to choose not to donate than to give time ($\chi^2 = 9.02$, $p < .05$), and low-moral-organization participants were 43 times more likely not to donate than to give time ($\chi^2 = 21.86$, $p < .05$). In addition, the choice probability contrasts showed that participants in the low-moral-prime condition were 5.7 times more likely to choose giving cash than giving time ($\chi^2 = 6.40$, $p < .05$). As we mentioned previously, these effects were qualified by the higher-order moral-identity prime × moral-organization interaction. To explore the moral-identity prime × moral-organization interaction, we estimated two separate multinomial logit models within the low-moral-organization (American Marketing Association) and the high-moral-organization (American Red Cross) conditions. These two models contained the control variables and the main effect of the moral-identity-prime manipulation. We found no statistically significant choice contrasts in the low-moral-organization condition; however, in the high-moral-organization condition, we found a significant moral-identity effect ($\chi^2 = 7.26$, $p < .05$). We examined the choice contrasts and found that men in the high-moral-organization condition were 4.3 times more likely to choose not to donate than to give time ($\beta = 1.47$, $\chi^2 = 3.96$, $p < .05$). We also found that being in the high-moral-identity condition of the high-moral-organization condition increased the likelihood that participants would choose to give time over money by 458% ($\beta = -1.719$, $\chi^2 = 6.08$, $p < .05$). In Figure 3, we graphed the number of people who chose to give time, to give cash, or not to donate as a function of the moral-prime and moral-organization manipulations. The pattern shows that the main effect of the moral-organization manipulation is heightened by the moral-prime condition such that when moral identity is primed, participants self-report a greater propensity to give time than to give money, but this is the case only when the organization is a moral organization that assists in being responsive to the social needs of other people. This pattern emerges even when we control for age, gender, religious participation, impression management, and participants' general perceptions of the value of their time (as in Study 1b).

Discussion of Study 3

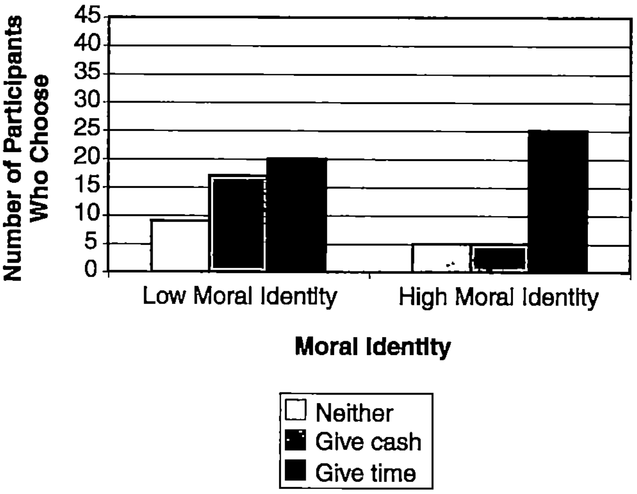
Study 3 builds on our previous studies by providing causal evidence for the effect of moral identity on preferences for giving time versus money. Study 3 also bolsters our argument that these preferences emerge because of the self-

FIGURE 3
Study 3: Joint Effect of Moral Organization and Moral Identity on Choices to Give Time, Money, or Neither

A: Low-Moral-Organization Condition: American Marketing Association



B: High-Moral-Organization Condition: American Red Cross



Notes: High moral identity is the condition in which the moral self was primed.

reinforcing properties of giving time rather than money (as in Study 1a). We found that the self-importance of moral identity heightens the preference for giving time, especially when giving time benefits an organization that professes moral goals. Study 3 also rules out the possibility that other, nonmoral-related aspects (e.g., mere impression management, making friends at the volunteer facility, learning more about the organization) are driving the results. Finally, Study 3 provides additional evidence that the effect is bounded by efforts that reinforce moral properties of the self (activities and organizations whose goals are to respond to the needs of others).

General Discussion

Consumers may differ in their perceptions of and intentions to engage in various types of philanthropic behavior. The impact of identity on reactions to giving time and giving money is crucial from the points of view of potential donors, charitable and for-profit organizations, and society at large (Reed, Aquino, and Levy 2007). Thus, by examining how consumer reactions to donating time versus money affects both individual charitable giving intentions and perceptions of corporate philanthropy, the package of studies we presented herein makes a unique contribution to both social psychology and marketing. However, an important question is how organizations can use this knowledge to enhance brand and company identification and promote goodwill through the facilitation of community relations. We propose several ways that both charities and for-profit organizations can do so, and we highlight some theoretical conundrums about donating time versus money that may provide opportunities for further empirical study.

Consider the guidance that this set of studies gives to a manager of a charitable organization. A charity's goals consist largely of soliciting donations of time and money from consumers and organizations to help people in need. Study 1a establishes that high moral identifiers are more likely to choose to donate time rather than money to a charity, and Study 1b extends this effect to identification with the actions of hypothetical organizations. These findings have several important implications. First, charitable organizations should have explicit strategies for soliciting donations of both time and money because consumer perceptions and motivations may differ for each type of giving. In constructing such a strategy, charities should identify their specific needs of time and money for particular campaigns, create organizational structures to serve these needs, and target an appropriate consumer audience to achieve these goals.

A suitable organizational structure may entail having different people or subunits in charge of soliciting time and money and using separate budgets for the execution of each strategy. Employees in each unit would preferably have a particular interest in procuring either time or money, resulting from either individual differences (such as their own moral identity) or characteristics of their professional background. In targeting an appropriate consumer audience, charities could attempt to solicit time from people who are more likely to possess a highly self-important moral identity. This may involve identifying people who belong to organizations that are considered moral (e.g., a church organization, the Society for the Prevention of Cruelty to Animals), people who already give time (e.g., Big Brothers/Big Sisters), purchasers of products that are known for social responsibility (e.g., Ben & Jerry's ice cream), viewers of television shows or magazines with moral themes, and partnerships with corporations that either have a moral image or may be looking to adopt this image.

Second, how consumers can go about donating time and subsequent donations of time should be explicitly linked to the needs of the organization and should be clearly communicated through a charity's advertisements and solicitations. Charities want high moral identifiers to know whether time, and not just money, is needed to achieve their intended goals. This is particularly so because people who are most likely to engage in charitable giving may be more likely to express moral action that shows responsiveness to the needs of others (Gilligan 1982; Kohlberg 1969; Rest 1979). If a charitable organization needs donations of money to achieve its goals, it may want to emphasize (particularly to high moral identifiers) how this money will enable the charity to give time to help those less fortunate. Doing so may help activate the morality of the time dimension rather than focus on the amount of money given. Such a circumstance might arise in which money is needed to train specialized personnel, for the purchase of equipment, or for other instances in which direct consumer donations of time would be less useful. For example, medical personnel may need specialized equipment to treat people who are infected with diseases in third-world countries, and money for food, electricity, and so forth, may be needed. Likewise, victims of a hurricane may need money to purchase food and shelter.

Web sites provide at least one way to emphasize the giving of time. For example, the United Way prominently displays a "Volunteer" button above the "Donate" button on its Web site. The American Red Cross seems to emphasize the giving of money more on its site and gives personal examples of people who have contributed large amounts of money (but not time). However, most of the Red Cross's volunteering is done through local chapters, and links are provided from its Web site. The homepages of these local chapters emphasize volunteering to a greater degree, though they also note the positive moral benefits of giving money. For example, the Seattle American Red Cross Web site states (see http://www.seattleredcross.org/helpnow/index.htm), "By making a gift to the American Red Cross, we are enabled to provide assistance to people in need here in our communities.... [Y]our contribution means a great deal to the families who rely on the Red Cross to help them through some of the most difficult times of their lives." This statement makes the point that if a consumer gives money, others who work for the organization will be able to give time to help those in need.

Third, Study 3 indicates that charitable organizations may be able to affect donations of time versus money by exposing consumers to a morally relevant prime in an advertisement or a solicitation. For example, an advertisement could state, "You probably consider yourself a caring, compassionate, hardworking person, and the American Red Cross could really use your help in volunteering your time to project X which serves the less fortunate," or it could use a visual image of others donating to convey this effect. Charities can use a moral-identity prime in various contexts to affect the degree to which consumers self-identify with actions that reflect more investment of the self. Indeed, an organization that is not typically considered a charity may also be able to encourage the donation of time through the use of a prime. For example, a noncharitable organization that engages in a charitable drive (e.g., the Professional Golf Association Tour of America's "Drive to a Billion" campaign, the Ronald McDonald House charities) could potentially be perceived as possessing similar moral characteristics as an organization that is charitable.

Although for-profit organizations can use the same strategies as nonprofits in certain instances, they also have additional concerns about corporate reputation and building brand equity. If a corporation's employees donate time and if this contribution can be effectively linked in consumers' minds to the organization's identity and its products, this may result in increased reputation and brand equity effects. Recent research suggests that corporate philanthropy can generate positive moral capital among communities and stakeholders and that this moral capital contributes to shareholder wealth through acting as insurance-like protection of a firm's relationship-based intangible assets (Godfrey 2005). Other research shows that consumers' associations of corporate social responsibility affect product perceptions independently of associations of corporate ability (Dacin and Brown 1997). Our studies suggest that donations of time can amplify each of these effects. Moreover, donating time may have intraorganizational effects on employees as well. We address these issues in turn.

Study 1b finds that high moral identifiers are more likely to relate to organizations that donate time rather than money, suggesting that a company's organization donation program can affect employee morale, job satisfaction, and intent to stay with the organization. This is because people are likely to be recruited by and seek to work for organizations that are perceived as a good mutual "fit" (Chatman 1991). This effect may be particularly true for high-status employees who also possess a highly self-important moral identity, as in Study 2. Being able to act in accordance with values may make these people more satisfied by being able to give time rather than money, counteracting the time-constraint effects of organizational status. Thus, if an organization adopts a donation program in which higher-level employees are able to give time, the company could operate more efficiently and profitably because it is particularly disrupting and costly to replace these employees if they leave the organization. Research has also found that MBA graduates of top schools may be willing to accept a lower starting salary to work for a company that is more socially responsible (Montgomery and Ramus 2003).

Furthermore, because a corporation is often considered a reflection of its top managers (Hambrick and Mason 1984), executive commitment to a time-donation program may have a "trickle-down" effect to employees at lower levels of the organization. Lower-level employees may begin to believe that investment of the self through giving time is an important part of the organizational culture and that this mind-set should be adopted. This process could operate through contagion (Barsade 2002), through the desire to conform to organizational norms, or through other means. Indeed, recent research has shown that moral development and actions of corporate leaders can affect employee attitudes and moral behaviors (Schminke, Ambrose, and Neubaum 2005). Thus, there are ample opportunities for employees of high organizational status to set the tone for the moral actions of the rest of the organization by emphasizing the benefits of donating time.

For marketing managers of for-profit organizations, there are at least three distinct ways to increase brand equity through consumers' differential reactions to giving time versus money. First, managers should consider the "type" of brand a company possesses (e.g., its brand personality; see Aaker 1997) and determine whether this brand would benefit from associations of corporate donations of time. Certain brands may be viewed as possessing more "moral" associations or may already be known for their corporate social responsibility (e.g., Ben & Jerry's ice cream). Donation of corporate time may be particularly relevant to purchasers of these brands because of their identification with the investment of self made by the organization's employees (as in Study 1b). Conversely, donation of time could help a less typically well-regarded organization (e.g., a tobacco company) increase its perceived moralness.

Second, managers can use advertising, which could emphasize the link between a brand and the donation of company time to charitable causes, thus generating the transfer of more positive attitudes toward the brand (Brown, Homer, and Inman 1998; Burke and Edell 1989). Study 3 suggests that if the advertisement presents a strong enough moral prime so that consumers' moral identities are "activated," these positive brand perceptions should generalize to consumers beyond those who possess an inherently highly self-important moral identity. However, brand managers must also be cautious about appearing opportunistic in self-promoting their company's charitable deeds. If consumers make this negative inference, any positive brand equity effects may be lost. For example, a recent "Truth" television advertisement derided a tobacco company for donating $125,000 to a charitable cause and then spending more than $21 million to advertise its generosity. This apparent opportunism on the part of the company in spending 168 times as much on advertising its generosity relative to the donation itself would likely not result in generating much goodwill among its customers and the public.

Third, marketers can benefit from and attempt to manage the positive word of mouth (e.g., Balter and Butman 2005; Brown et al. 2005) and goodwill that accrue in the communities in which the company donates time. The benefits here may be particularly great for large companies with offices in multiple cities and/or major cities, thus increasing the number of consumers that can be reached through donating time. Key managerial strategies in this instance are to maximize the positive interactions between employees and the community organization (by ensuring that employees understand and enjoy their roles and, perhaps, inviting citizens in the community to join in the donation effort) and to generate positive press coverage of the events (by contacting local media and other civic organizations). Note that, ideally, each of these three strategies (brand personality, advertising, and word of mouth) should work together as part of the marketing mix to form a coherent strategy that attracts consumers to the brand as a result of the company's donation of time to charitable causes.

Conclusions

Answering the question of what determines a person's preferences to give time rather than money is difficult because role and occupational commitments impose varying social and economic costs on consumers who would otherwise prefer to give their time. Furthermore, consumers have idiosyncratic opportunity costs that may enter into their decision of how to best serve the public good. These observations highlight relatively unstudied questions in marketing; namely, how do individual, psychological, and situational factors influence the way consumers evaluate the desirability to either donate money or donate time for community service? The potential psychological ambivalence of how to give may be particularly acute in moral decision-making situations, in which being true to the moral self may be disadvantageous or require the sacrifice of other life or personal career goals. At the same time, the salience and self-importance of moral identity may be at least one internal mechanism that motivates some consumers to do rather than to pay.

APPENDIX
Moral Identity Measure

Listed below are some characteristics that might describe a person:

Caring, Compassionate, Fair, Friendly, Generous, Helpful, Hardworking, Honest, Kind

The person with these characteristics could be you or it could be someone else. For a moment, visualize in your mind the kind of person who has these characteristics. Imagine how that person would think, feel, and act. When you have a clear image of what this person would be like, answer the following questions.

I 1. It would make me feel good to be a person who has these characteristics.
I 2. Being someone who has these characteristics is an important part of who I am.
S 3. I often wear clothes that identify me as having these characteristics.
I 4. I would be ashamed to be a person who had these characteristics. (R)
S 5. The types of things I do in my spare time (e.g., hobbies) clearly identify me as having these characteristics.
S 6. The kinds of books and magazines that I read identify me as having these characteristics.
I 7. Having these characteristics is not really important to me. (R)
S 8. The fact that I have these characteristics is communicated to others by my membership in certain organizations.
S 9. I am actively involved in activities that communicate to others that I have these characteristics.
I 10. I strongly desire to have these characteristics.

Notes: I = internalization, S = symbolization, and R = reverse coded

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The Influence of Incidental Affect on Consumers' Food Intake

Although incidental affect has been shown to influence both attitude and purchase behavior, it has not been extended to actual consumption. This research investigates whether specific affective states influence food consumption and whether this influence is moderated by factors such as information and the nature of the product (hedonic versus less hedonic). The authors show that an integrative mood management and mood evaluation framework accounts for this relationship more effectively than a self-regulation explanation. A preliminary test and two lab studies show that people eat larger amounts of hedonic foods (buttered popcorn and M&M's) when they are in a sad state than when they are in a happy state and that this effect is attenuated when nutritional information is present. In contrast, they tend to eat larger amounts of a less hedonic product (raisins) when they are in a happy state than when they are in a sad state. The authors discuss implications for responsible marketers, health professionals, and health conscious consumers in the context of campaigns and individual efforts.

People often associate consumption-related behaviors with the affective state they are experiencing. Indeed, incidental affect—the affect consumers imbue from their environment in isolation to the task at hand—has been shown to influence in-store shopping (Woodruffe 1997) and in-home food choice (Hetherington and MacDiarmid 1993). In addition, although prior research has effectively examined how health claims and nutrition labels influence health beliefs and purchase intentions (Balasubramanian and Cole 2002; Kozup, Creyer, and Burton 2003; Moorman et al. 2004), a pressing issue for the Food and Drug Administration (FDA; 2003) is whether such information can realistically influence food intake on a single eating occasion. Given the U.S. obesity epidemic, understanding how incidental affect influences food intake and whether its influence can be moderated through warnings or nutritional labeling is an important topic.

Consumption research has tended to focus on issues such as how advertising (Wansink and Ray 1996), packaging (Wansink 1996), and stockpiling-induced promotions (Ailawadi and Neslin 1998) influence a person's consumption. A consistent finding across these studies is that a person's food consumption can be nontrivially influenced by various environmental elements, such as advertisements, promotions, and container size. Given the susceptibility of consumption to contextual factors and the pervasiveness of incidental affect, valuable insights might be gained from combining these two research areas and studying the influence of affect on consumption.

Although no food companies would want to discourage consumers from purchasing their products, it is in their interest to understand how moods influence consumers' food consumption. For example, overconsumption can lead not only to weight gain but also to rapid satiation and delayed repurchasing (Inman 2001). Over the long run, helping consumers better control their consumption could also help promote more favorable attitudes toward the brand and company. This may result in what Rothschild (1999) refers to as a "win–win" policy-sensitive solution for both companies and consumers.

In this research, we examine how different discrete affective states (sad versus happy) influence consumption and whether this relationship is attenuated by nutritional information and product type (hedonically rewarding versus less so). Our research makes five important contributions. First, we show that incidental affect—sadness and happiness—influences food intake within a general population and not simply within select segments (Greeno and Wing 1994). Second, we show that nutritional information can effectively moderate the impact of incidental affect on consumption. Third, we find that the consumption patterns for people experiencing different emotions are dependent on the nature of the food product (hedonic versus less hedonic). Fourth, we establish the theoretical framework underlying this phenomenon and show that an integrative mood management and mood evaluation framework (Andrade 2005) accounts for this relationship more effectively than a self-regulation explanation (Baumeister, Heatherton, and Tice 1993). Fifth, we offer useful implications for public policy officials, health care professionals, and consumers who are interested in controlling their food intake. In turn, these findings become relevant to brand managers who are increasingly being held accountable for contributing to the obesity problem (Ellison 2003).

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In developing the framework for this investigation, we extend Andrade's (2005) work in three important ways. First, we manipulate specific, discrete emotions (sadness, happiness) rather than generalized positive and negative affective states. Most research in marketing has adopted a valence-based approach to conceptualize affect and has examined the impact of general positive and negative affective states on decision processes. However, recent research has demonstrated the importance of examining specific emotions rather than global (positive–negative) feelings (DeSteno et al. 2000; Garg, Inman, and Mittal 2005). Our work contributes to this growing body of literature.

Second, we show that whether a cue is interpreted as mood lifting or mood threatening depends on the person's affective state. Our findings suggest that happy people treat hedonic products, such as buttered popcorn and M&M's, as a mood-threatening cue and avoid them, whereas sad people consider them mood uplifting and overconsume them (relative to a control group). This is especially important from the perspective of policy makers who want to understand how consumers react to different food products to develop appropriate policies and interventions. In addition, we show that there is interdependence between mood state and product type (hedonic versus less hedonic), or a "product–affect asymmetry."

Third, in contrast to Andrade's (2005) work, we posit that though gender may be an important variable in understanding consumption patterns, it fails to be the distinguishing factor when restrained eaters (dieters) are removed from the sample. In keeping with much of the research in the consumption domain, Andrade shows a significant gender effect. Specifically, he finds that whereas women consider a product such as chocolate to have mood-changing properties, men do not. Our work provides an important caveat to this research and suggests that consumption as a mood management tactic seems to be prevalent in the general population, regardless of gender.

We begin by summarizing relevant research on incidental affect and consumption and by contrasting the affect regulation and affective evaluation model (Andrade 2005) with a self-regulation failure explanation. In support of affect regulation, three studies show that when people are sad, excessive consumption of a hedonic product is tied to mood management motivations, but lower consumption of a less hedonic product is linked to affective evaluation. We observe the reverse pattern for happy people. We close with a discussion of the implications for four key stakeholder groups: managers, policy makers, health care professionals, and consumers.

Literature Review and Hypothesis Development

Although it is well established that incidental affect influences many dimensions of consumer behavior (Mayer et al. 1992), most of the existing research has focused on the influence of generalized negative or positive affect on aspects of consumption, such as food preference and choice in specific groups (e.g., clinically depressed people, dieters). There is little nonanecdotal evidence that specific affective states (e.g., sadness and, especially, happiness) influence the amount of food consumed in the general population (cf. Tice, Bratslavsky, and Baumeister 2001).

Recent research has hinted at a possible relationship between affect and consumption. For example, Woodruffe (1997) examines compensatory consumption in women's shopping behavior. Her findings suggest that shopping offers a means of compensation for some women when they are in a negative affective state. Participants in Mick and DeMoss's (1990) study also suggest that certain food products (e.g., ice cream, hot tea) are a form of compensatory consumption. However, Wansink, Cheney, and Chan (2003) suggest that this effect can vary according to a person's mood state. Importantly, in contrast to the current research, these studies focus on preference for certain food products and do not try to ascertain whether affect influences the amount consumed. We now discuss the theoretical framework that helps us establish the link between affect and consumption.

The Integrative Affective Evaluation and Affect Regulation Framework

Andrade's (2005) integrative approach suggests that rather than treating affective evaluation (e.g., mood congruency) and affect regulation (e.g., mood management theory) theories as being in opposition to each other, certain contingencies can explain when one versus the other will be operational. Affective evaluation theories propose that people's current states influence their evaluations, judgments, and actions in an affect congruent manner. That is, people experiencing positive affect have a favorable appraisal of the environment, which results in congruent behavior and promotes action or a more proactive approach. In contrast, people experiencing negative affect have a less favorable appraisal of the environment, which results in congruent behavior and impedes action or leads to a more passive approach. Conversely, affect regulation theories propose a more dynamic outlook in which people experiencing sadness look for options to repair their mood state, leading to a more action-oriented approach. Similarly, people experiencing happiness are motivated to maintain their mood state, leading to a more passive approach in which they refrain from action to avoid potentially mood-threatening consequences of those behaviors.

What are the circumstances under which one of these two processes, affect regulation and affective evaluation, dominate? Andrade (2005) proposes multiple moderators but suggests that the most critical aspect that separates the two processes is whether the activity/behavior that the person is considering has mood-changing properties. He argues that when mood-changing cues are present in the environment, people will be more likely to use mood management strategies. When mood-changing cues are not salient, people will be more likely to follow affective evaluative strategies and assess things/actions in congruence with their mood state. Tice, Bratslavsky, and Baumeister (2001) make a similar argument and find that people respond to distress by eating more fattening, unhealthful snack foods, but this tendency is reversed if they believe that eating will not change their mood state. Other studies similarly suggest that people engage in mood management when a mood-changing cue is present (e.g., Mick and DeMoss 1990; Woodruffe 1997).

Overall, these studies provide some support for the mood management hypothesis in the presence of a mood-changing cue/opportunity (e.g., information, comfort food, shopping) and suggest that people in a sad state try to move away from their state, whereas people in a happy state try to be more protective of their state. As a result, we argue that happy people are more likely to try to maintain their positive state by refraining from consuming food items that might make them regret their consumption later (e.g., fattening or otherwise unhealthful food items). In effect, people in a happy affective state should avoid overeating both because they do not need food to feel emotionally better and because they do not want it if the consequences could make them feel emotionally worse. This suggests that they should consume less of a hedonic, mood-altering product than sad people.

Wansink, Cheney, and Chan (2003) find that happy people prefer more healthful food products. If we examine this finding from the perspective of Andrade's (2005) framework, it seems likely that happy (versus sad) people will be more likely to consume a food product whose perceived hedonic properties are not dominant or are relatively less prominent and, thus, does not possess the same perceived mood-changing properties as a hedonic product, such as M&M's or buttered popcorn. This is because in the absence of a mood-changing cue, the affective evaluative processes come into play, which should lead to people behaving in congruence with their mood state. Thus, happy people's positive evaluations of the environment and the product should lead them to eat more, whereas sad people's negative evaluations of the same should result in lower consumption. Thus, we expect the consumption pattern for a hedonic product to reverse for a relatively less hedonic product.

Compared with happy and sad people, those in a neutral affective state have neither a need for mood repair nor a need for mood maintenance. Thus, their consumption levels should fall somewhere in between those of sad and happy people for both the products. That is, they should consume more than happy people but less than sad people for a hedonic food product, and they should consume less than happy people but more than sad people for a less hedonic food product. This leads to our first two hypotheses. We test H_1 in the preliminary test and two studies, and we test H_2 in Study 2.

> H_1: Incidental affect influences people's consumption levels, such that for a hedonic product, (a) consumption levels are lower for people in a happy state than for people in a sad state, and (b) consumption levels for people in a neutral affective state fall between the levels for sad and happy people.
>
> H_2: Incidental affect influences people's consumption levels, such that for a less hedonic product, (a) consumption levels are lower for people in a sad state than for people in a happy state, and (b) consumption levels for people in a neutral affective state fall between the levels for sad and happy people.

A critical distinction between this theory and the self-regulation failure hypothesis (e.g., Baumeister, Heatherton, and Tice 1994) is in the consumption pattern that is predicted for these affect conditions across product types (hedonic versus less hedonic). The self-regulation stream of research has often shown how obese people, dieters, depressed people, and clinically ill people (e.g., those suffering from bulimia nervosa) are likely to break down under emotional stress and overconsume (e.g., Greeno and Wing 1994). Thus, although both theories predict that sad people should consume more of a hedonic product than happy people, the predictions diverge when a less hedonic product is considered. Unlike the self-regulatory failure explanation, the integrative framework (Andrade 2005) predicts that sad people should consume less when they are offered a less hedonic product. The reverse should occur for happy people because the more positive evaluation of the environment should lead to greater consumption of the less hedonic product. This is a key distinction from self-regulation theory (e.g., Baumeister, Heatherton, and Tice 1994), which makes the same overconsumption prediction for sad people, regardless of product hedonicity. This leads to our third hypothesis, which we test in Study 2:

> H_3: Incidental affect influences people's consumption levels, such that consumption levels are (a) higher for sad people when they are offered a hedonic product than when they are offered a less hedonic product and (b) higher for happy people when they are offered a less hedonic product than when they are offered a hedonic product.

Another robust finding in the self-regulation domain suggests that women are likely to be more restrained eaters than men and that they are more concerned about dieting and weight (Hawkins, Turell, and Jackson 1983; Rozin, Bauer, and Catanese 2003). Andrade (2005) also uses gender as one of the main factors that distinguishes whether a product such as chocolate is a mood-changing cue (he assumes that this pertains only to women). To examine this relationship further, the preliminary test and the two studies examine the influence of gender on a person's consumption. In the discussion, we elaborate on why gender might not be an important variable when examining the general population. We also explore self-regulation failure in consumption as an alternative explanation in light of our results and discuss how the integrative framework more fully accounts for the pattern of results.

Preliminary Test of the Affect–Consumption Link

The objective of the preliminary test is to examine the main effect of mood on the amount consumed. That is, this test examines how affect influences people's consumption quantity of a hedonic product, such as buttered popcorn.[1]

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[1] We pretested buttered popcorn along with six other products (potato chips, M&M's, red grapes, an oatmeal bar, raisins, and a mixed-fruit cup) to examine people's perceptions of the products' hedonic and health aspects. The seven food products represented a mix of positive and negative nutritional value (e.g., fat content, calorie/unit, vitamins). For each product, participants indicated their level of agreement on a seven-point scale for six statements:

Specifically, we study whether manipulating sadness and happiness through the content of a movie has the predicted effect on consumption. A substantive advantage of using full-length feature films to manipulate affect is that it enables us to mimic the natural environment (e.g., the movie-going experience) in a laboratory. Another advantage is that examining the effect in a relatively naturalistic setting enables us to focus on specific affective states (e.g., sadness and happiness) rather than global affect. As discussed previously, we expect that sad people will attempt to repair their negative state, leading them to consume more than happy people.

Procedure

To induce the relevant affective state, participants watched full-length movies that evoked positive or negative affect. We used a one-factor, two-level, within-subjects, counterbalanced design in which half of the participants saw a happy movie and a sad movie on two consecutive days and the other half saw them in the reverse order. Participants were recruited for the two-hour, two-day study and were told that we were interested in their evaluations of the movies. They were not told which movies they would be viewing. We induced the sad state by having participants watch *Love Story*, and we induced the happy state by having them watch *Sweet Home Alabama*. We selected these films because they could be matched on several key variables, such as running time, quality (critic ratings), box office success, and broad content area (i.e., both are based on a romantic relationship). Subsequent manipulation checks established that the two movies were successful in inducing the relevant affect. The section on manipulation checks discusses this issue in greater detail.

Thirty participants completed the study by participating on both days. On arriving for the study, participants were randomly assigned to one of two viewing rooms. The viewing rooms were set up with couches and stuffed chairs and were decorated to look like family rooms. Five to eight people at a time viewed the movies, which were shown on a large 28-inch television using a VCR. Before the movie began, each participant was given a freshly popped, large bucket of microwave popcorn (buttery and salty) and a selection of noncaloric drinks (diet soda or water). Each bucket of popcorn had been weighed before the movie began, and each contained an average of 180 grams of popcorn. Pretests indicated that this size was large enough that people would not finish the popcorn.

At the conclusion of each movie, participants were asked to indicate their assessments of the movie (1 = "sad, negative, not uplifting," and 9 = "happy, positive, uplifting"). The same questions were then asked with respect to their affective state. They were also asked to describe what it was about the movie that made them either happy or sad. After they left, their container was weighed, and this weight was subtracted from the original weight to determine the amount of popcorn consumed. The procedure for the following day was the same, except that people saw the alternate movie, and after they completed the affect questionnaire at the end of the film, they were further asked to indicate on nine-point scales (1 = "unaware, little attention," and 9 = "aware, much attention") the extent to which they paid attention to how much they ate and were aware of how much they ate. They were also asked to indicate at which movie (*Love Story*, *Sweet Home Alabama*, or neither) they thought they ate more popcorn.

Results

Because we used the content of the movies to manipulate affect, it was first necessary to determine that the two movies had the intended effect of inducing either sadness or happiness. Cronbach's alpha for the three affect measures provided adequate convergence ($\alpha_{movie} = .65$, $\alpha_{affect} = .59$). We then averaged the three measures to form a composite score for the perception of the movie and a composite score for the affective state the movie induced. Paired t-tests conducted on these scores verified that the movie scores for the happy movie versus the sad movie were significantly different ($M_{sad} = 4.50$ versus $M_{happy} = 7.02$; $t_{29} = 4.60$, $p < .01$). Similarly, the difference in the scores for the affective state induced by the two movies was significantly different ($M_{sad} = 4.10$ versus $M_{happy} = 7.33$; $t_{29} = 7.03$, $p < .01$).[2] Thus, the movies were successful in manipulating the desired emotions.

To test whether consumption levels differed across the two movies for the same people, we conducted a repeated measures analysis of variance (ANOVA) in which movie was a within-subjects factor and order, session time, and gender were covariates. As we predicted, participants consumed significantly more (28% more) while watching the sad movie than while watching the happy movie ($M_{lovestory} = 124.97$ grams versus $M_{sweethome} = 97.97$ grams; $F(1, 26) = 15.87$, $p < .01$), but none of the other main effects or interactions were significant. That is, this analysis revealed that the differences did not vary with the order of the movie ($F(1, 26) = .58$, $p = .46$), gender ($F(1, 26) = .36$, $p = .55$), or the session time (afternoon, evening; $F(1, 26) = 1.31$, $p = .26$).

A reason some people overeat is because they fail to monitor their intake effectively. For example, people may

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"makes me feel good," "tastes great," "lifts me up when I am down," "is pleasurable," "is comforting," and "is healthy." Five of these items (except "is healthy") constituted the hedonic factor, and we averaged them to give the hedonic score for each food product. Reliability for all products was acceptable ($\alpha > .78$), except for potato chips ($\alpha = .59$), which we dropped from further analysis. Buttered popcorn (4.09) and M&M's (4.22) had the highest means on the hedonic dimension, and the difference between the two means was not significant ($t = 44$, n s.) Furthermore, buttered popcorn and M&M's were both perceived as more hedonic than the oatmeal bar and raisins ($p < .05$). Moreover, M&M's were perceived as more hedonic than even the mixed-fruit cup ($t = 2.96$, $p < .05$). On the health dimension, both M&M's and buttered popcorn were perceived as less healthful than all the other alternatives ($p < .0001$) but comparable to each other (2.23 versus 1.87; $t = .90$, n.s.). Overall, these results establish that both buttered popcorn and M&M's are perceived as the most hedonically rewarding but the least healthful products among those tested.

[2] We also tested the differences on the sad–happy dimension alone, and the analysis indicated that for both the movie and the affect induced, the differences were significant ($t_{29} = 2.95$, $p_{movie} < .01$; $t_{29} = 9.29$, $p_{affect} < .01$).

tend to overeat while watching television, during which they are typically not conscious of their consumption (Baumeister, Heatherton, and Tice 1994). However, differences in monitoring do not account for our results, because participants did not monitor their consumption any differently across the two movies. Because we tested differences in consumption in a within-subjects setting, this test makes a persuasive argument in support of our thesis.

Using actual program content to manipulate affect has important practical implications because it shows how the content of a movie, television program, or perhaps even reading material can induce affect that has subsequent consumption implications. Conversely, using content to manipulate affect has its drawbacks. First, the treatment and consumption were concurrent, which makes it more difficult to argue a cause–effect relationship between the two. Second, some study participants might have known that *Sweet Home Alabama* is a happy movie and that *Love Story* is sad, so it could be argued that the mere anticipation of the forthcoming affect might have influenced consumption. Third, although the manipulation checks established that the movies were successful in manipulating the relevant affect, a movie cannot maintain the same affective tone for the entire period (100-plus minutes), and a movie necessarily associates mood with specific content. However, although mood manipulations are typically confounded with content, feelings have been shown to guide judgment and behavior independent of explicit thoughts (Pham 2004). Finally, a limitation of the current test is the low alphas for the self-reported affect measures. To address the concerns that can arise in such a naturalistic setting, Study 1 examines all three specific states—sadness, happiness, and neutral—using a different manipulation. Furthermore, Study 1 examines whether nutritional information acts as a moderator for this effect.

Study 1: How Nutritional Information Influences Mood-Related Consumption

One of the objectives of Study 1 is to replicate the findings of the preliminary test and to extend them by including a neutral state and testing H_1 in a more tightly controlled setting with a different affect manipulation. This establishes the robustness of our results. Second, the inclusion of the neutral affective state provides a baseline for the effect. This is important because differences in consumption across the positive versus neutral affect conditions support the mood management hypothesis over the self-regulatory failure explanation (the latter predicts no differences across the two conditions, because both happy and neutral people should be equally in control). A third objective of this study is to determine whether the presence of nutritional information attenuates the influence of affect on consumption.

The Moderating Role of Nutritional Information

The observation that consumption can be widely influenced by product-related factors is further supported by the findings related to nutritional labeling and product labeling (Balasubramanian and Cole 2002). Lenahan and colleagues (1973) find that consumers believe that they benefit from nutritional information not only because they can choose a better product but also because they believe that it makes food manufacturers more accountable for the nutritional quality. When information is easy to understand, consumers tend to use it (e.g., Moorman 1990, 1996).

Although people may pay attention to nutritional data and may value positive nutrients, they are sometimes willing to trade off nutrition for taste in various product categories (Baltas 2001). Although researchers have examined the use of nutrition information, they have not examined how the focus on nutrition information might vary under different affective states. Moreover, they have not linked it to consumption. This possible linkage is becoming increasingly important. For example, restaurants are under pressure to provide nutritional information to their patrons (McLaughlin et al. 2003), and the FDA has begun negotiations with the restaurant industry to lay out standards for nutritional information displays in restaurants (Wilde 2003). However, it is not known whether such legislation will have the intended impact on consumption, because it is not known whether appropriate nutritional information can moderate consumption.

Research has shown that people tend to focus on negative information more than positive information (Russo et al. 1986); thus, we focus on a hedonic, negative, nutrient-rich product. We argue that when nutritional information is made salient to consumers, it will cause the consumption levels for the three groups (happy, sad, and neutral) to converge. Specifically, providing nutritional information should make the negative consequences of overconsumption more salient to people and negate any mood-changing benefit they might have otherwise expected from the consumption. Essentially, the negative consequences of consumption should outweigh the positive consequences when the (negative) nutritional information is made salient. Because happy people are already avoiding consumption to protect their affective state, we expect a decrease in consumption for sad and neutral people when they are exposed to negative nutrition information for a hedonic food product (which has negative nutrients), such as buttered popcorn:

> H_4: The presence of nutritional information for a hedonic product attenuates the influence of incidental affect on individual consumption levels, such that happy, sad, and neutral people tend to converge to similar levels of consumption.

Procedure

Participants were recruited from the undergraduate population of a large mid-Atlantic university. One hundred ten students participated in the study in exchange for extra credit. We used a 3 (affective state: sad versus neutral versus happy) × 2 (nutritional information: absent versus present) between-subjects design. Participants were randomly assigned to one of the six cells and were scheduled in groups of five. On arrival, they were assigned seats in separate cubicles in a large room.[3] The complete task took between 30 and 40 minutes.

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[3] This controls for an alternative, social influence explanation for the results in Study 1.

The study consisted of three parts: the information examination task and/or the filler task, the affect-inducing part, and a story-reading task. To disassociate the nutritional information task from the affective induction, the former was presented to the participants as a "style-of-processing" study, and the latter was presented as a separate "life-events" survey. The participants completed the style-of-processing study in which they either examined the label with nutrition information for a bag of unpopped popcorn along with a filler task (information-present condition) or just answered the filler task (information-absent condition). The label was designed to resemble an actual product label as closely as possible. After examining the label, participants indicated how easy it was to process the information and how much fat, saturated fat, and calories they thought a serving size of popcorn has compared with similar amounts of other food products they consume.[4] The filler task consisted of questions about the manner in which participants carried out mental tasks, such as learning words, reading, and imagination (Fitzsimons and Shiv 2001). The participants were given the information before the affect induction to avoid the mood state influencing their information-processing capabilities.

We then administered the incidental affect manipulation to participants using a methodology that Lerner and Keltner (2001) refined. The manipulation consisted of two questions. The first question asked participants to describe three or four things that make them happy/sad, depending on the assigned affect condition. The second question then asked them to describe in detail the one thing that makes (or made) them most happy/sad. They were encouraged to describe the incident in such a way that another person reading the description might experience the same affect. Participants in the neutral condition were asked to first describe three to five activities they did that day and then to describe in detail what their typical day was like and the activities they undertook on a routine day (e.g., Garg, Inman, and Mittal 2005). Emotions elicited by such manipulations last long enough to exert influence on subsequent tasks (Lerner and Keltner 2001).

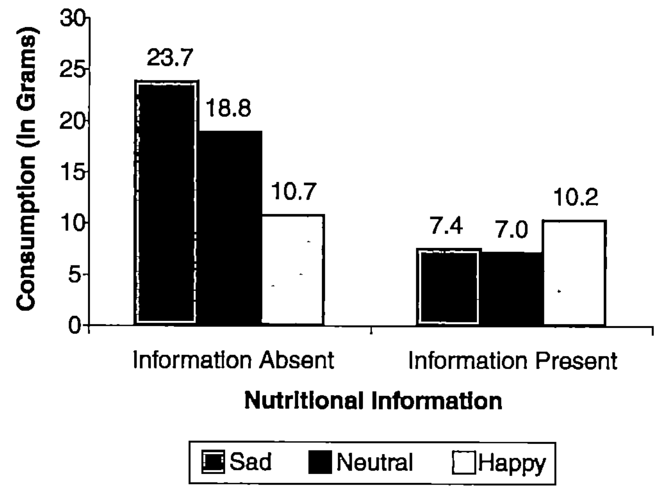
The final task was called an "imagination and information-processing" study. It required participants to read a two-page event narrative and rate a series of statements on seven-point scales (1 = "strongly disagree," and 7 = "strongly agree"). The statements assessed how well they could relate to the story, how happy/sad they thought the story was, and how interesting they found the narrative to be. The purpose of this task was to give participants time to consume popcorn, which had been offered to them as a refreshment along with a choice of diet soda and water after the affect induction. We pretested the narratives for their affective tone and designed them to help maintain each participant's affective state (e.g., a participant in the happiness condition was asked to read a happy event description).[5] The happy story described the chance reunion of four friends after many years and an enjoyable evening they spent together. The sad story talked about the then-recent Columbia shuttle disaster and the feelings of loss and grief the families of the astronauts were experiencing. Finally, the neutral narrative described a day in the life of a typical undergraduate student, focusing on daily activities, such as getting ready, attending classes, going to the gym, and watching television.

Toward the end of the final task (i.e., the imagination and information-processing study), participants answered additional questions about the perceived taste of the popcorn, the time elapsed since their last meal, and their average frequency of popcorn consumption. They were also asked to guess the objective of the studies and whether they thought that the different studies were connected in some way. Eight participants partially guessed the purpose of the study, and we excluded them from the analysis. After the completion of the study, participants were thanked for their participation, and their bags of popcorn were collected. As in Study 1, each bag of popcorn had been individually weighed beforehand and was reweighed to obtain the post-consumption weight.

Results

Although we expected that people in a happy affective state would consume less than those in a sad affective state, we also believed that these differences would be attenuated when people were given nutritional information. As Figure 1 indicates, the results were consistent with our expectations. To test whether these differences are significant, we conducted a 3 (affective states: sad, neutral, and happy) × 2

FIGURE 1
Moderating Role of Nutritional Information on the Influence of Affect on Consumption



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[4]The means for the nutrients were between five and six on a nine-point scale, indicating that participants perceived buttered popcorn as similar or only slightly higher in fat, calories, and saturated fat than most products they consume.

[5]For participants who read the happy story (n = 10), the happiness score was higher than the sadness score (5 80 versus 2.13; $t_9 = 5.78$, $p < .001$), whereas for participants who read the sad narrative (n = 10), the sadness score was higher than the happiness score (2.26 versus 4 63; $t_9 = 3.96$, $p < .01$). As we expected, participants who read the neutral narrative (n = 9) showed no difference between their happiness and their sadness scores (3.22 versus 3.40; $t_8 = .33$, n.s.).

(nutritional information: present versus absent) ANOVA, in which grams consumed was the dependent variable and perceived taste, level of hunger, and gender were covariates. As H_4 predicted, a significant main effect of the presence of nutritional information on consumption levels emerged ($F(1, 100) = 13.33$, $p < .01$). Specifically, the average consumption level for participants with no information was 17.98 grams, whereas consumption for those who were given the nutritional information was only 8.25 grams. The main effect for incidental affect was not significant, but as we predicted, the interaction between affect and information was significant ($F(2, 100) = 4.41$, $p < .05$). That is, when nutritional information was not salient, people in the sad condition consumed the most, and those in the happy condition consumed the least. In this model, both taste and hunger emerged as significant factors ($F(1, 100) = 5.96$, $p_{taste} < .05$; $F(1, 100) = 5.96$, $p_{hunger} < .05$). This indicates that though hungry people and those who perceive the popcorn as tastier might consume more, it does not explain our results. Furthermore, as we expected, gender was not a significant factor ($F(1, 100) = .05$, $p = .82$).

H_1 predicted that incidental affect would influence consumption level such that people in a sad state would eat the most, those in a happy state would eat the least, and those in a neutral state would fall in between these states. To test this, we focus on the information-absent group. As Figure 1 shows, participants in the sad condition consumed the most, whereas those in the happy condition consumed the least (23.7 grams versus 10.7 grams). As we also predicted, those in the neutral condition fell between the happy and the sad groups in terms of their consumption (18.8 grams). One-tailed pairwise comparisons in the information-absent condition reveal that the difference in consumption between the sad and the happy groups is significant ($t_{104} = 3.00$, $p < .01$), as is the difference in consumption between the happy and the neutral groups ($t_{104} = 1.92$, $p < .05$), in support of the mood management hypothesis. The difference between the sad and the neutral groups is not significant, but it is in the right direction; people in the sad condition consumed 25% more on average than those in the neutral condition. Overall, the results show that the consumption levels are in a descending order from sad to neutral to happy people, as H_1 predicted.

We also predicted that the presence of nutritional information would attenuate the impact of affect on consumption such that the consumption levels of the three groups would tend to converge (H_4). When (negative) nutritional information was provided, consumption levels dropped for participants in the sad condition (7.4 grams versus 23.7 grams) and the neutral condition (7.0 grams versus 18.8 grams), but levels were unaffected in the happy condition (10.2 grams versus 10.7 grams). It appears that happy people are already managing their consumption, so providing such information has little impact. In contrast, the product information prevented people in the sad and neutral affect conditions from overconsuming this product. Thus, nutritional information serves as a boundary condition to the influence of affect on consumption, in support of H_4.

Using a more tightly controlled setting in which the affect induction precedes consumption, Study 1 tests and finds support for H_1 and H_4 and not only shows that incidental affect significantly affects consumption levels at the individual level but also establishes nutritional information (when salient) as a moderating factor for the influence of affect on consumption. Although differences emerged between the happy and the neutral participants in the information-absent condition, Study 1 was not designed to provide direct evidence to distinguish one theoretical mechanism from the other. Study 2 replicates and extends the results from the preliminary study and Study 1 and establishes the theoretical underpinnings responsible for this phenomenon.

Study 2: How Product Type Influences Mood-Related Consumption

One of the objectives of Study 2 is to validate H_1 further by replicating the consumption pattern we found in Study 1 for buttered popcorn with another hedonic product (M&M's). This will establish the robustness of our results and rule out product-specific effects. Second, and more important, Study 2 tests H_2 and H_3 by examining the pattern of consumption across the three affective states (sad, neutral, and happy) with a less hedonic product (raisins) as well.[6] This is important because the comparison of the effects across a positive and a negative nutrient product will help us understand the underlying theoretical mechanism—the integrative framework versus the self-regulation failure—that is responsible for the influence of affect on consumption.

Procedure

Participants were recruited from the undergraduate population of a large southern university. We used a 3 (affective state: sad versus neutral versus happy) × 2 (product type: hedonic M&M's versus less hedonic raisins) between-subjects design. One hundred thirty-nine students who had indicated they were not currently following a diet participated in the study in exchange for extra credit. To avoid the demand effects associated with asking potential participants if they were on a diet before the study, we allowed all students to participate, and we eliminated from the analysis those who indicated that they were on a diet at the end of the study (n = 48).

The procedure for this study was similar to that followed in Study 1. Participants were randomly assigned to one of the six cells and were scheduled in groups of eight. On arrival, they were assigned seats in separate cubicles in a large computer lab. As part of a preliminary questionnaire, participants completed baseline measures of affect (the Positive and Negative Affect Schedule; see Watson, Clark, and Tellegen 1988). After the preliminary questionnaire, we manipulated incidental affect using the same methodology as in Study 1 (Lerner and Keltner 2001). One difference in the "imagination and processing study" was that the Columbia shuttle disaster had receded somewhat from the public memory. Thus, the sad narrative now described the tragic loss of seven children in a fire, along with the emotional responses of eyewitnesses. Again, we pretested the sad and neutral narratives for their affective tone.[7]

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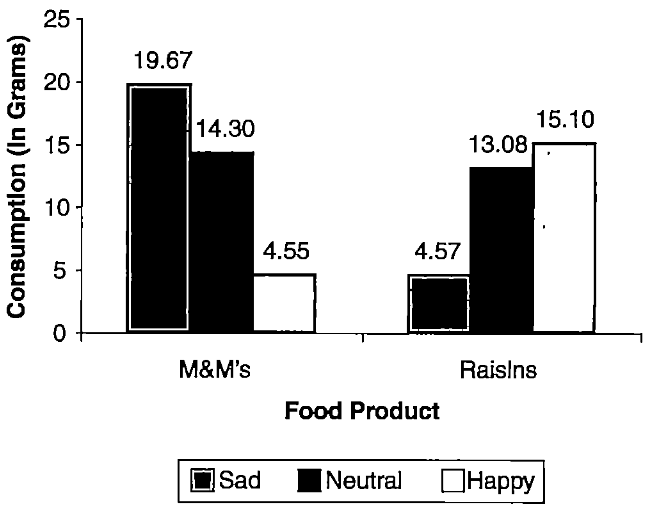
[6] In the same pretest, products such as the mixed-fruit cup, red grapes, and raisins were perceived as more healthful alternatives. Raisins are notable because, of these three products, raisins were perceived as the least hedonic food product ($p < .05$, for all except oatmeal bars); indeed, they were perceived as relatively healthful (they ranked third on the health dimension).

To control for potential confounds, participants answered a series of questions in the final questionnaire about the time elapsed since their last meal, the extent to which they felt hungry or full before and after the studies, their dieting status, and whether they tried to restrict or monitor their consumption. Finally, to collect emotion manipulation measures, participants reported the feelings they experienced when writing about an autobiographical event pertaining to a specific emotion (sad, happy, or neutral). To avoid revealing our interest in specific emotions, the form asked about 18 affective states, only 12 of which were of interest. "Gloomy," "upset," "downhearted," and "sad" constituted the sadness factor (α = .94); "unemotional," "indifferent," "neutral," and "unaroused" constituted the neutral factor (α = .82); and "happy," "elated," "joyful," and "amused" constituted the happy factor (α = .83). Responses ranged from "did not experience the emotion at all" (0) to "experienced the emotion more strongly than ever before" (8). Participants also answered questions about whether the emotion they felt was negative/positive and pleasant/unpleasant on a nine-point scale. Individual ANOVAs on reported experience of sadness (F(2, 136) = 154.26), happiness (F(2, 135) = 88.20), and neutral (F(2, 135) = 22.77) indicated strong emotion induction (p < .0001). Participants then answered a set of demographic measures pertaining to their sex, age, and race/ethnicity. After the completion of the study, participants were thanked for their participation and dismissed. As in Study 1, each bowl of food product was individually weighed before and after consumption to obtain the amount consumed (in grams).

Results

Although we expected that different emotion groups in the hedonic unhealthful product condition (M&M's) would replicate the pattern found in Study 1 (i.e., happy people would consume less than sad people), the key contrast in this study is in the relatively less hedonic but healthful product condition (raisins). On the basis of the integrative framework, we argue that the consumption patterns should reverse for raisins such that happy people will consume more than sad people. As Figure 2 indicates, the results are consistent with our expectations.

FIGURE 2
Moderating Role of Product Type on the Influence of Affect on Consumption



To test whether these differences are significant, we conducted a 3 (affective states: sad, neutral, and happy) × 2 (product type: M&M's versus raisins) ANOVA, in which hours since last meal, level of hunger at the beginning (Hunger 1) and at the end (Hunger 2) of the study, self-restraint items (e.g., participants' tendency to "eat sensibly in front of others and splurge alone" and how many pounds over their ideal weight they felt they were at their maximum weight), gender, and age were covariates. The dependent variable in the analysis was the amount of food product consumed (in grams). Neither the main effect of incidental affect nor that of product type was significant, but as we expected, the interaction between affect and product type was significant (F(2, 125) = 5.14, p < .01). None of the covariates were significant. In particular, similar to the previous two studies, the effect of gender on consumption was not significant (F(1, 125) = 1.15, p = .29). This bolsters our conclusion that in the general population, consumption of hedonic alternatives is used to manage the mood state that a person is in, regardless of gender.

H_1 and H_2 predicted that affect and product type would interact such that happy (versus sad) people would consume more of the less hedonic food product (raisins), and sad people would consume more M&M's, thus replicating the findings from Study 1 and the preliminary test. As Figure 2 shows, participants in the sadness condition consumed more M&M's than those in the happiness condition (19.67 grams versus 4.55 grams), and this difference was significant in a one-tailed t-test (t_{42} = 2.60, p < .01). This pattern is reversed for raisins: Happy participants consumed the most, and sad participants consumed the least (15.10 grams versus 4.57 grams; t_{45} = 1.88, p < .05). People in the neutral condition fell between the happy and the sad groups in terms of their consumption for both products ($M_{M\&M's}$ = 14.30 and $M_{raisins}$ = 13.08). In addition, in a one-tailed t-test, the difference between the sad and the neutral groups is significant for raisins (4.57 versus 13.08; t_{49} = 1.65, p = .05), and though it is not significant for M&M's (p = .15), it is in the right direction; people in the sad condition consumed 38%

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[7] For participants who read the sad narrative (n = 22), the sadness score was higher than the happiness score (6.27 versus 1.06; t_{21} = 38.78, p < .0001), and for the neutral narrative (n = 17, M_{sad} = 3.31 versus M_{happy} = 3.00, n.s.), there were no differences between the two scores.

more than the average consumption for those in the neutral condition, as in Study 1. Moreover, neutral people consumed more M&M's than happy people (14.30 grams versus 4.55 grams), and this difference was significant in a one-tailed t-test ($t_{39} = 1.61$, $p = .05$). Thus, as H_1 and H_2 predicted and in line with the integrative framework, the consumption levels across the affective states are in the predicted direction for both products, with the levels in a descending order from sad to neutral to happy for M&M's and in the reverse order for raisins. Next, we discuss the theoretical mechanism underlying these results.

H_{3a} proposed that if the integrative framework rather than self-regulation failure were the responsible mechanism, sad people should consume more of the hedonic product than the less hedonic one. As we predicted, a one-tailed t-test finds that the consumption levels for sadness are significantly different across the two products ($t_{50} = 2.79$, $p < .01$). This offers direct evidence for the integrative framework and against self-regulation failure. Furthermore, H_{3b} predicted that happy people's consumption would be higher for the less hedonic product than for the hedonic product, and the results of a one-tailed t-test support this prediction ($t_{37} = 1.73$, $p < .05$). Thus, our results support H_3 and suggest that the integrative framework accounts for the findings rather than a breakdown in a person's self-control.

Discussion

Although prior research has investigated both incidental affect and consumption, our research illustrates the need to examine these two factors in conjunction. Given the pervasiveness of incidental affect and the necessity of consumption, it is important to understand how affect influences consumption and what responsible managers, health professionals, and consumers can do to attenuate or even negate its potentially deleterious influence. Across the preliminary test and the two studies, we manipulated specific emotional states using different methods (movies versus written induction) to test our hypothesis that in the absence of negative nutritional information, sad people consume more of a hedonic product than relatively happier people. The preliminary test used across-movie differences to determine whether this key relationship between affect and consumption emerged in a within-subjects context. We found that the same people consumed approximately 30% more when they watched a sad movie than when they watched a happy movie. More than three-quarters of the participants exhibited an increase in consumption in the sad film versus the happy film, and one-half of the participants exhibited a substantial (more than 20 grams) increase.

A key purpose of Study 1 was to test whether nutritional information could attenuate affect's influence on consumption. Whereas sad and neutral people showed a substantial decline in their consumption, happy people seemed to be uninfluenced by nutritional information. Thus, it appears that happy people are already avoiding consumption, and the presence of nutritional information does not drive their consumption any lower, as the mood management hypothesis predicts. Conversely, sad people acted consistently with what would be expected if people wanted to indulge themselves to try and overcome their negative state by consuming more (in the information-absent condition).

Study 2 helps disentangle the theories—the integrative affective evaluation and affect regulation framework versus self-regulation failure—by offering evidence to suggest that the integrative framework accounts for the findings, not a breakdown in self-control. The results from Study 2 support the affective evaluation process of the integrative framework by contrasting two products that differ on the hedonic dimension. In the case of raisins, happy people consumed more than sad people. This is consistent with the predictions of the affect regulation framework, which suggests that in the absence of mood-changing cues, affective evaluation dominates, leading people to behave in congruence with their mood state (i.e., happy people have positive evaluations and tend to eat more, whereas sad people have negative evaluations and tend to eat less). Thus, this study generalizes the results across different product categories and provides critical insight into the theoretical process behind this phenomenon.

Furthermore, the studies examined whether gender influences consumption, as the findings in the self-regulation domain suggest. However, no gender effects were evident in any of our studies. This implies that managing affect is a phenomenon independent of gender and that though gender might play a role when we consider restrained eating (dieters), in the general population, both men and women use consumption as a way to manage their affective state.

The link between mood and consumption has been puzzling for health care professionals, consumers, managers, and policy makers who are interested in better controlling food intake. Although recent work in comfort foods has shown that people are more likely to turn to comfort foods when they are in negative moods than when they are in positive moods, this research has not indicated how much they eat in these specific situations. The following sections discuss implications of our findings for different stakeholders—namely, managers, public policy makers, consumers, and health care professionals (see Table 1).

Implications for Managers

For farsighted food marketers, the goal is not simply to trick people into gorging themselves on a single occasion. Although this might appear to be the one-period game-theoretic solution to the unscrupulous food marketer, it may well backfire in a long-term, multiperiod setting. The potential for increased sales volume may be overwhelmed by satiety effects (e.g., Inman 2001) and lower brand equity when consumers eventually realize the ploy. When addressing food and overeating, it is important for firms to develop profitable win–win solutions to help consumers better control what they want to eat. No company would want to modify a product in a way that discourages consumers from purchasing it or consuming it. However, it may be in a company's best interest to help consumers better control how much they consume in a single setting. For example, the results from a survey of 770 North Americans indicated that 57% of the participants would be willing to pay up to 15% more for portion-controlled items (Wansink and Huck-

TABLE 1
Implications for Consumers, Managers, Public Policy Makers, and Health Professionals

	Consumers and Health Care Professionals	Managers	Public Policy Makers
General View	•People overeat food for many reasons, including to manage mood. They eat to repair bad moods and to maintain good moods. •Overeating because of mood can have positive short-term and negative long-term consequences. •By eating less, people can probably still moderate negative moods.	•Overconsuming a food on a single occasion can lead to satiation, burnout, and longer repurchase periods. •The marketing goal is to increase intake incidence, not volume per occasion. •There is potential to develop profitable win–win opportunities by helping people eat less per occasion.	•Overeating is not always unintentional, particularly in good moods. •Nutritional information has its place but will be more effective with some people (those in bad moods) than with others. •It is important to encourage moderation and not avoidance.
Finding 1: Incidental Affect: People tend to eat more when sad than when happy.	•If people are in a sad mood or if they are taking medication for depression, they can (1) eat more healthful foods and (2) preplate their portions to prevent unintentional overeating. •People should realize that the guilt that can follow overeating can exacerbate negative moods. •People should remind themselves that they can still enjoy the mood-related benefits of food by eating less and enjoying it more.	•Targeting "sad" media programming may increase consumption incidence relative to competing products. •Such targeting should be accompanied with a nutrition message or an eat-less-enjoy-it-more message. •Drug companies selling antidepressants could consider a warning that depression can lead to overeating and to choose products and portion sizes wisely when taking medication.	•FDA warnings for antidepressant medications could also warn of the danger of overeating in such a condition. •Special attention needs to be given to situations in which people are most likely to be sad and possibly overeat. These might include various health facilities, selected cafeterias, and situations in which certain affect might be induced (e.g., movies).
Finding 2: Information Moderation: Nutrition information moderates consumption for sad people but not for happy people.	•Nutritional information influences how much people eat when they are in sad moods more than when they are in happy moods. •When people eat in a sad mood, they should either check nutritional information or simply try to eat a more healthful food.	•Nutritional information (in restaurants and on packages) may be a win–win solution. It can decrease overeating among people who want to eat (those in a bad mood) but not among those who are there to celebrate. •There is less need for concern that restaurant labeling will make people in a good mood enjoy their food less.	•Despite assertions to the contrary, nutritional information can decrease intake under some conditions and may have a role if labeling the nutrition information on restaurant menus or on packaged goods. •Developing strategies to make nutritional information salient is an important issue.
Finding 3: Product–Affect Asymmetry: Effects are asymmetric across healthful and less healthful hedonic foods.	•People need to be aware of the tendency to overeat certain products depending on their mood state. There is a danger they can still overeat (even if it is a relatively healthful product), if they are not warned about this tendency. •People should be encouraged to eat what they want but to do so in small quantities. Although switching to more healthful foods is wise, people still need to eat smaller portions.	•Product burnout is possible for both unhealthful and relatively healthful products, though in different consumer groups (sad versus happy). •Focus on information related to all products in targeted mood situations, such as during programming that is often associated with affect (e.g., news shows, movies, dramas).	•Do not focus efforts only on indulgent foods, such as snack foods and desserts. Salience of nutritional information seems relevant for all products. •An education and legislative focus should include both healthful and unhealthful foods because both have the potential to be overeaten.

abee 2005). Moreover, it could help prevent product "burnout" and also help promote more favorable attitudes toward the brand and company.

Our findings raise the issue of how marketers might leverage something as exogenous as a person's mood. Although marketers cannot (thankfully) easily manipulate people's moods, there are many ways they can locate people who are likely to be in either good or bad moods. An approach is to target media or programming that attracts or instills the targeted mood. For example, although situation comedies might attract or induce a happy mood, news programs, dramas, or documentaries might attract or induce a more negative mood. Similarly, the location or events that people attend may induce different moods. People eating at the cafeteria of a "dead-end" job may be in a more negative mood than those going out to eat at a restaurant of their choice. To help reduce overconsumption, marketers can provide nutritional information, or they can simply remind consumers to "eat less, and enjoy it more." For pharmaceutical companies selling antidepressants, including a warning note that sad mood can lead to food overconsumption provides a public service and underscores another implied benefit of their product.

Implications for Policy Makers

Policy makers and enforcers, including the FDA and the Federal Trade Commission, have been perplexed as to how to determine their role and that of companies in the area of obesity. Most of their efforts have focused on labeling and food choice. Although much of the information indicates that labeling does not have a sizable impact on purchase behavior, our findings offer a silver lining that though nutrition information may not influence what people eat, it can influence how much certain people eat. In addition, our results suggest the potential effectiveness of nutrition labeling among people in negative moods and in certain situations in which people are most likely to be sad and possibly overeat (e.g., while watching a sad program/movie). Our findings also point to a product–affect asymmetry in which happy people can overeat relatively healthful foods (versus the control). Thus, an important question for policy makers is to assess the effectiveness of information for different products and for people in different mood states.

Research has already established that particular information formats can be easier for consumers to understand and use (Russo et al. 1986). Our findings support the idea that if information is easy to understand, it should be made available to the consumer whenever possible, including places such as restaurants and movie theatres. Away-from-home dining raises an issue of nutrition labeling in restaurants, which is of relevance to the FDA (Wilde 2003). It can help decrease overeating among people in bad moods but not influence those who want to celebrate.

However, nutritional information should not be considered a panacea, because consumers do not always notice the information and eating behaviors are often not cognitively involving. In Study 1, to test the effect of nutritional information, it was made more salient than is usually the case in real life. This can potentially be considered a limitation because people do not always pay attention to the information even if it is present; thus, an important issue in the real world is to make information salient. Notably, the FDA recently seems to have achieved that with trans-fat information. It has mandated that beginning in 2006, all food manufacturers must make information about trans-fats available. This has received a lot of press and has gained salience in public consciousness. The same end can hopefully be achieved by promoting the findings here.

Implications for Consumers and Health Care Professionals

People overeat for many reasons, including trying to manage their mood. They eat to repair bad moods and to maintain good ones. In light of this deliberate role that eating plays, it is unreasonable to suggest that consumers simply not eat when in a bad or good mood. The results of this research show that education (information) has the greatest impact on people in a negative mood. Yet in addition to suggesting that people in negative moods are more susceptible, it also implies that they might not realize how much they actually eat (preliminary test and Study 1).

Therefore, an important implication of our findings for consumers is that they understand the role of affect in everyday consumption and how it can be better controlled to help improve their welfare. Prior research has established that recognizing the source of affect might not always be helpful, because it can lead to overcorrection (DeSteno et al. 2000). Fortunately, overcorrection in the food consumption domain is desirable in the general population (the focus of our research) and in special groups, such as dieters and overweight people (though not for groups on the other end of the spectrum, such as anorexics).[8] When people become aware of the link between affect and consumption, they are more likely to take deliberate steps to be more conscious of how much they eat. For example, they could preplate their food, move the serving bowl or bag into the kitchen, eat only when sitting at a table, or preportion snacks.

From the consumer perspective, another important question that arises from these results is that because it is now known that people in a sad mood might use food as a hedonic reward, is it feasible to make people aware of this tendency and then to direct them toward more innocuous domains for repairing their mood, such as watching movies, exercising, or talking to a friend? Furthermore, should happy people be worried about the overconsumption of relatively healthful foods (product–affect asymmetry)? These are important questions for both health care professionals and researchers because they have major implications for dealing with rising obesity and associated health costs, and they need to be examined in greater detail.

Limitations and Further Research

In our studies, we focused on the consumption patterns of people who are experiencing different affective states. We generalize the findings across different product categories and across different settings (seminaturalistic and lab) using different manipulations (movies and autobiographical write-up). However, to enhance the external validity of our findings, it would be useful to examine this phenomenon in a field setting, such as at a theater. Validation of the results in such a setting would provide greater credibility and generalizability.

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[8] We thank an anonymous reviewer for pointing out this caveat.

Although we examined two moderating factors—the presence of nutritional information and the nature of the product—it is probable that other factors moderate the affect–consumption relationship. For example, further research could examine how awareness of the source of the affect (internally versus externally generated awareness) moderates this relationship. This factor has been examined in social psychology settings, but it would be useful to examine this in a more consumer research–oriented setting to ascertain its efficacy. Moreover, it would be worthwhile to observe how information moderates the consumption of a less hedonic food product, such as raisins. Another related issue for further research is to examine whether guilt due to consumption of a hedonic product influences our results. Specifically, does information salience make guilt more salient and thus reduce overconsumption in sad people? Another direction for further research would be to examine the dependence of our results on the relationship between the construct of hedonicity and nutrition. For example, what is the consumption pattern for a food product that is low in both hedonic aspect and nutrition, such as white rice, or high in both, such as low-fat ice cream?

Pham (2004) draws on a vast array of affect literature and comments on the "logic of feelings." He argues that contrary to common belief, relying on affect to guide judgments and behavior is not necessarily detrimental in nature and that it can actually be useful. Further research should examine the long-term consequences of consumption (e.g., eating, shopping) undertaken by people to manage their mood state. Although for some consumers, such as restrained eaters, using consumption to manage mood might lead to self-defeating behaviors (Leith and Baumeister 1996), it seems plausible that in the general population, it might be an efficient and, in the long run, an innocuous solution to deal with mood management issues and maintain a healthful, balanced outlook on life.

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CALL FOR PRACTITIONER NOMINATIONS

— 2·0·0·7 —

Charles Coolidge Parlin Marketing Research Award

The American Marketing Association and its Foundation along with The Wharton School announce the annual call for nominations for the 2007 Charles Coolidge Parlin Marketing Research Award. The award was established in 1945 by the Philadelphia Chapter of the AMA and The Wharton School in association with the Curtis Publishing Company to honor persons who have made outstanding contributions to the field of marketing research. Established as a memorial to Charles Coolidge Parlin, who is recognized as a founder of marketing research, the Parlin Award is today a preeminent national honor. Nominees may be either practitioners or academicians in the field of marketing research who meet the following award criteria (as adopted by the Parlin Board of Governors, September, 1996). Please be advised that the Parlin Board is only accepting nominees in the practitioner category this year.

The Charles Coolidge Parlin Marketing Research Award is the oldest and most distinguished award in the field, honoring Charles Coolidge Parlin by recognizing distinguished academics and practitioners who have demonstrated outstanding leadership and sustained impact on advancing the evolving profession of marketing research over an extended period of time. Specifically this impact might be reflected in one or more of the following:

1. New concepts, methods, and models for measurement and analysis that expand the capabilities of organizations to achieve a better understanding of markets, customers and consumers.
2. Creative integration of existing methodologies and an understanding of information needs resulting in more widespread use and/or appreciation of marketing research.
3. Demonstrated leadership resulting in stimulating the effective use and value of marketing research and market based knowledge.

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Please provide detail on how the nominee has impacted the profession of marketing research as outlined in the award criteria:

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2. Creative integration of existing methodologies and an understanding of information needs resulting in more widespread use and/or appreciation of marketing research

3. Demonstrated leadership resulting in stimulating the effective use and value of marketing research and market based knowledge

Please feel free to add any additional information, including biography / curriculum vitae, list of publications/citations, etc. Also, please feel free to attach additional pages.

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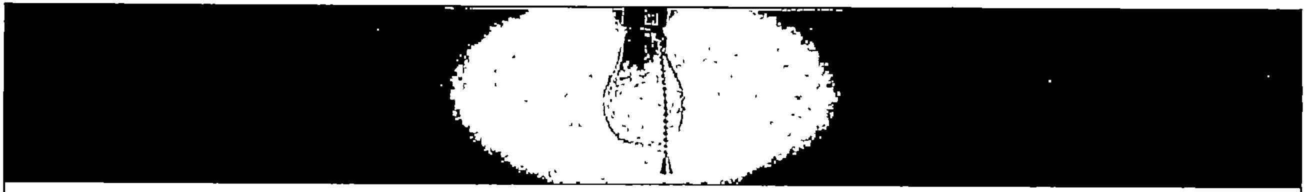

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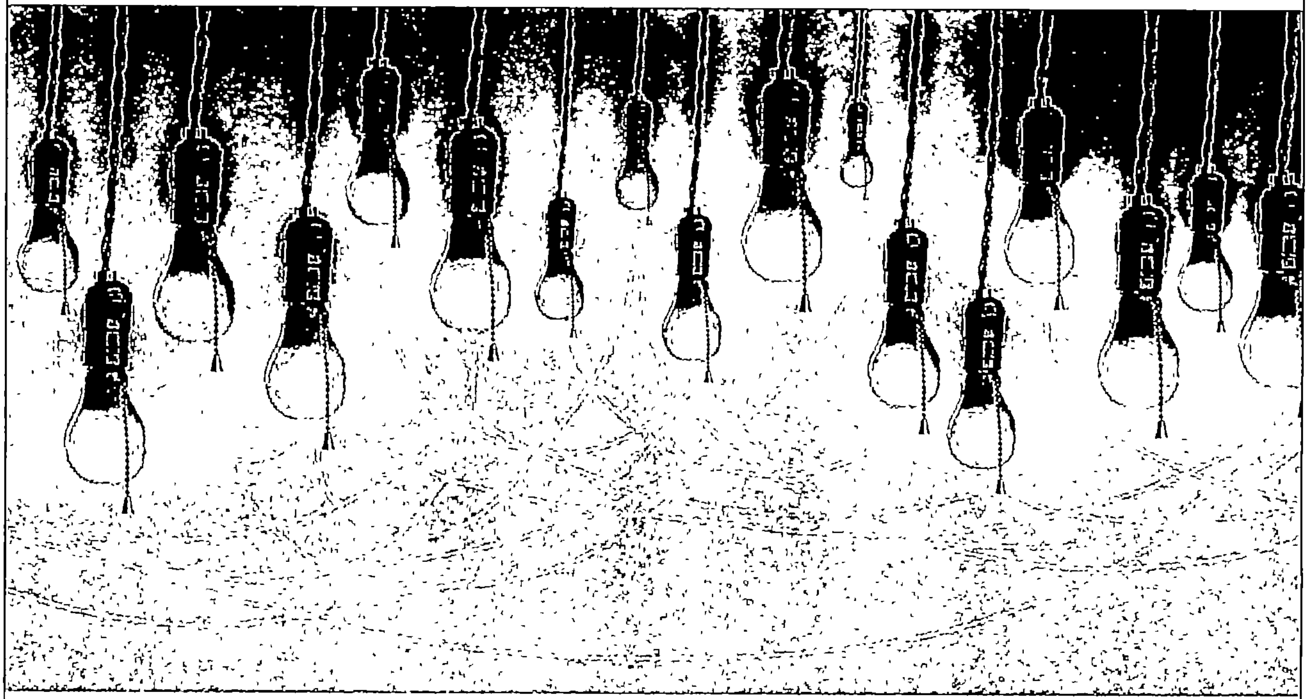

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SHETH FOUNDATION/JOURNAL OF MARKETING AWARD

The recipients of the 2006 Sheth Foundation/Journal of Marketing Award, which is administered through the American Marketing Association Foundation, are **Rajendra K. Srivastava**, **Tasadduq A. Shervani**, and **Liam Fahey** for their article "Market-Based Assets and Shareholder Value: A Framework for Analysis," which appeared in the January 1998 (Vol. 62, No. 1) issue of the *Journal of Marketing* (*JM*).

Nominations for the award were solicited from members of the *JM* Editorial Review Board, and a selection committee of *JM* former editors (Ruth Bolton, Roger Kerin, and Robert Lusch) made the selection. The award is given to honor articles that have made long-term contributions to the *discipline of marketing*. The award recognizes scholarship based on the benefits of time and hindsight and acknowledges contributions and outcomes made to marketing theory and practice. This year, the committee considered all articles published in *JM* between 1997 and 2001. The committee also weighs information obtained from letters of nomination and citation analyses.

The article is significant in that it develops the concept of "market-based" assets, or assets that arise from the interaction between the firm and its external environment; foremost among these are customer relationships, channel relationships, and partner relationships. Importantly, the article also develops a coherent conceptual framework to integrate marketing and finance. At the center of this framework is the focus on using marketing tools and resources to accelerate and enhance cash flows and to reduce their volatility, both of which lead to improved shareholder value. The conceptual framework developed in this article has become a major frame of reference for executive education and strategic market planning in organizations across a wide variety of industries. It has also spurred empirical research on the topic of market-based assets and the relationship between marketing investments and shareholder value.

The Sheth Foundation/Journal of Marketing Award was established through the generosity of the Sheth Foundation. The criteria for selection include the quality of the article's contribution to theory and practice, the article's originality, its technical competence, and its impact on the field of marketing. Articles eligible for the award must have been published at least five years but not more than ten years earlier.

The award, which carries both a plaque and a cash prize, was presented at the American Marketing Association's 2007 Winter Marketing Educators' Conference, held February 16–19, at the Sheraton San Diego Hotel & Marina.

- Rajendra K. Srivastava is Roberto C. Goizueta Chair in e-Commerce and Marketing, Goizueta Business School, Emory University.
- Tasadduq A. Shervani is Associate Professor of Marketing, Cox School of Business, Southern Methodist University.
- Liam Fahey is Adjunct Professor of Strategic Management, Babson College, and a partner in the Leadership Forum, Inc.

Of note, this is the first article ever to win all three of *JM*'s major article awards—that is, Sheth Foundation/Journal of Marketing Award (2006), Harold H. Maynard Award (1998), and Marketing Science Institute/H. Paul Root Award (1998).

HAROLD H. MAYNARD AWARD

Eyal Biyalogorsky, **William Boulding**, and **Richard Staelin** have been selected as the recipients of the 2006 Harold H. Maynard Award for their article "Stuck in the Past: Why Managers Persist with New Product Failures," which appeared in the April 2006 (Vol. 70, No. 2) issue of *Journal of Marketing*. The article was chosen by members of the *JM* Editorial Review Board for its significant contribution to *marketing theory and thought.*

The award, which carries both a plaque and a cash prize, was presented at the American Marketing Association's 2007 Winter Marketing Educators' Conference, held February 16–19, at the Sheraton San Diego Hotel & Marina.

- Eyal Biyalogorsky is Associate Professor of Management, Graduate School of Management, University of California, Davis.
- William Boulding is Professor of Marketing and Associate Dean for the Daytime MBA Program, The Fuqua School of Business, Duke University.
- Richard Staelin is Edward and Rose Donnell Professor of Business Administration, The Fuqua School of Business, Duke University.

MARKETING SCIENCE INSTITUTE/H. PAUL ROOT AWARD

Gary F. Gebhardt, **Gregory S. Carpenter**, and **John F. Sherry Jr.** have been selected as the recipients of the 2006 MSI/H. Paul Root Award for their article "Creating a Market Orientation: A Longitudinal, Multifirm, Grounded Analysis of Cultural Transformation," which appeared in the October 2006 (Vol. 70, No. 4) issue of *Journal of Marketing*. The article was chosen by members of the *JM* Editorial Review Board for its significant contribution to the *advancement of the practice of marketing.*

The award, which carries both a plaque and a cash prize, was presented at the American Marketing Association's 2007 Winter Marketing Educators' Conference, held February 16–19, at the Sheraton San Diego Hotel & Marina.

- Gary F. Gebhardt is Assistant Professor of Marketing, College of Business Administration, University of South Florida.
- Gregory S. Carpenter is James Farley/Booz Allen Hamilton Professor of Marketing Strategy and Director of the Center for Market Leadership, Kellogg Graduate School of Business, Northwestern University.
- John F. Sherry Jr. is Raymond W. & Kenneth G. Herrick Professor of Marketing and Department Chair, Mendoza College of Business, University of Notre Dame.

Min Ding

A Theory of Intraperson Games

A wide variety of theories across disciplines posit the existence of multiple inner preferences (selves, drives, or agents) within each person, whose conflicts must be resolved for a person to reach a decision. Despite their strong validity, these theories have not been incorporated into mainstream management science literature because of their qualitative nature. In this article, the author proposes a theory of intraperson games (TIG) to fill this important gap. Building on social welfare literature and standard (multiperson) game theory, the TIG defines two types of intraperson players, and each has a unique strategy set. The first type, the efficiency agent, attempts to maximize the total utility for the entire set of selves that reside in a person's mind. The second type, the equity agent, strives to balance the utilities that each of these selves receives. The TIG states that an individual decision is the outcome of the strategic interaction between the efficiency agent and the equity agent. Thus, standard consumer utility theory is a special case of the TIG if the role of the equity agent is ignored. A mathematical apparatus is provided for the TIG and is defined in a way similar to standard (multiperson) game theory. As a general quantitative theory, the TIG can be applied to many different contexts across disciplines, including, but not limited to, management science. The author demonstrates one such application for variety-seeking behavior and shows that stochastic variety seeking is a mixed-strategy equilibrium in an intraperson game. Key theoretical insights from this applied model are subsequently validated in an empirical study.

"An angel on one shoulder and a devil on the other" is a familiar American folk expression that captures moments of conflict that most people have experienced at one time or another. It recounts the anguish of a person who is pulled in opposite directions by two conflicting preferences (the angel on one shoulder tells him or her to do one thing, and the devil on the other shoulder tells him or her to do the opposite).

This folklore exemplifies a school of thought that underlies a wide variety of theories across disciplines that posit the existence of multiple inner preferences (also called selves, drives, and agents in different literature) within each person, whose conflicts must be resolved for a person to reach a decision. Such thinking begins with Sigmund Freud's (1923) structural theory and also includes Carl Jung's (1959) unconscious and persona theory, Erik Erikson's (1968, 1970) stage concept, Henry Murray's theory of needs (see Shneidman 1981), Charles Brenner's (1982) conflicting-mind theory, Marvin Minsky's (1986) "the society of minds," and the theory of reasoned action (Ajzen and Fishbein 1975, 1980).

Despite their strong validity, these theories are mostly qualitative. To the best of my knowledge, no general quantitative theory models individual decisions as the outcome of the (strategic) interaction of multiple selves. The lack of such a rigorous framework has limited the theories' descriptive and prescriptive power for at least two reasons. First, in general, qualitative theories are not particularly powerful in some complex situations and cannot offer precise insights. Second, they are poorly suited to serve as building blocks for quantitative theories based on individual decision making (e.g., economics, management science). Without a quantitative framework for multiple selves, economics and management science simply assume that people are governed by their singular selves (i.e., utility function).[1]

This article proposes a general quantitative framework to fill this important gap based on the following intuition: The state-of-the-art quantitative approach to modeling strategic interactions among multiple parties uses (multiperson) game theory. If the roles of multiple selves (within each person) can be formalized to characterize them similarly to the ways (e.g., payoff, actions, knowledge, belief) that define each player in a multiperson game, it should be possible to develop a modified version of multiperson game theory to capture individual decision making. Thus, I propose a theory of intraperson games (TIG) to model explicitly the strategic interactions of people's multiple selves.

To demonstrate the utility of this new theory, I implement a TIG model for variety-seeking behavior. Variety seeking refers to "the tendency of individuals to seek diversity in their choices of services or goods" (Kahn 1995, p. 139) and typically appears within the context of switching among options. In the context of multiple selves, the parsimonious TIG model provides a theoretical explanation for stochastic variety seeking as an equilibrium strategy in an intraperson game. It also identifies specific conditions in which a consumer seeks variety and then empirically validates these conditions.

The rest of this article is organized as follows: The relevant literature is first reviewed on multiple selves. Then, the TIG is proposed, followed by an application for variety-

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[1] For exceptions, see the discussion in the next section.

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seeking behavior. Finally, the article concludes with a general discussion and directions for further research.

Relevant Literature

Modeling individual decision making as an intraperson game is meaningful only if existing theoretical and empirical literature supports two premises. First, multiple selves must exist inside a person's mind, and their interactions must lead to observed individual behavior. Second, at least some of these selves must be capable of choosing strategies that improve their own utilities and (possibly) reach equilibrium outcomes. The first premise provides the requisite environment for intraperson games, because by definition, any game requires more than one player. The second premise makes it relevant to study people's behavior in a game theoretical framework because standard game theory has little descriptive or prescriptive utility in situations in which the players are not intelligent enough to formulate long-term beneficial strategies. Therefore, literature that supports these two premises is reviewed.

Multiple Selves and Individual Decision Making

Two streams of literature posit that people's minds consist of multiple selves, each with its unique characteristics. Research in psychology and psychiatry attempts to understand people's decision making and provide descriptive (diagnostic) and prescriptive solutions, whereas research in artificial intelligence (AI) investigates the construction of the human mind to inform its creation of machine intelligence. I highlight the structure theory (Freud 1923) of the first stream and the society of minds (Minsky 1986) of the second to provide a foundation for the TIG.

Many psychological and psychiatric theories espouse the notion that each person possesses multiple and often conflicting selves (or preferences) and that a decision requires the resolution of these conflicts. Many notable researchers, such as Anna Freud (1936), Fenichel (1941), Hartmann and Kris (1945), Hartmann, Kris, and Loewenstein (1946, 1949), and Brenner (1975, 1982), have extended Sigmund Freud's (1923, 1926) influential structural theory. In "The Ego and the Id," Freud (1923) proposes three major functional centers of the mind. The id represents instinctual drives, is largely biological, and resides in the unconscious, which makes it, by nature, primitive, self-centered, and antisocial. Freud also identifies two id-related drives, erotic and aggressive—though subsequent work suggests that any given person can possess various drive derivatives (Brenner 1982)—that aim toward whatever feels good at a given time, regardless of reality. The superego consists of a group of moral imperatives that enable the person to pass judgment about what is right and wrong and act as an observer or critic. Some refer to the superego as conscience because it represents self-judgment, self-punishment, and ideal aspirations and, in general, functions at an unconscious level. Although the superego is strongly influenced by social standards of the culture in which the person is raised, it is not an internal replication of such standards but rather is individual in nature, in that it represents the internalization of a person's exposure to the ideals and standards of other important people. In general, the demands emanating from the superego conflict with those from the id. Finally, the ego mediates the internal and external environments and reconciles the drives of the id and the ideal aspirations of the superego on the basis of an assessment of realistic consequences (Brenner 1982). Therefore, ego might be viewed as a person's own self; it is learned through interactions with important people, through which it acquires methods to cope with difficult situations. The ego also goes through an endless process of adaptation, reconciliation, and integration, so each person develops his or her own set of compromise rules to respond to inner and external pressures.

Similar thinking also has emerged in the field of AI. Although this field continues to evolve, Minsky (1986), one of the founders of AI, argues in *Society of Minds* that minds are not singular entities but rather are composed of a large number of "miniminds" (which he calls "agents"). Each agent has a specific and limited role, and the interaction of these agents results in the person's observed intelligence. Minsky suggests a hierarchical structure, such that a higher-level agent chooses which lower-level agent the person uses during a given situation. However, Minsky does not differentiate the roles of those agents or indicate how higher-level agents might make choices; he asserts only that they occur in a hierarchical structure. Thus, his theory does not provide a specific framework for constructing quantitative models of intelligent individual decision making.

Although both streams of literature are qualitative, they argue convincingly that multiple selves exist and that interactions among these selves lead to decisions. Thus, although no theories provide a quantitative framework to capture such interactions, existing theories offer the building blocks for intraperson games. Specifically, the proposed TIG incorporates the roles of the three distinctive types of selves (id, ego, and superego) from structure theory and the concept of agents in a hierarchical relationship from Minsky's theory.

Ability to Identify Equilibrium Strategies

The idea of multiple selves within each person is a necessary but not sufficient condition to support a game theoretical approach to modeling individual decision making. That is, the TIG can offer little descriptive or prescriptive utility if the multiple selves cannot formulate strategies to improve the individual selves' utilities and potentially reach equilibrium outcomes. As is theorized in both psychiatry and AI, most selves/agents in isolation possess limited or no intelligence and cannot conduct the sophisticated thinking (e.g., backward induction) that classic game theory requires. However, two alternative research streams indicate that selves may be capable of identifying better strategies and equilibrium outcomes. According to evolutionary theory (Darwin 1859) and its offspring—evolutionary game theory (Maynard Smith 1982) and evolutionary psychology (Buss 1999)—an entity could identify better strategies with essentially no intelligence. In addition, another research stream argues that such strategies can be achieved with learning through even basic intelligence (Fudenberg and Levine 1998).

Evolution theory states that only two elements are necessary for an "optimal" outcome: mutation and selection. Even in the absence of intelligence, random mutation coupled with strong selection pressures leads to seemingly rational evolutionary outcomes. As an extension, evolutionary game theory (Maynard Smith 1982; Weibull 1995) demonstrates that multiperson games require no intelligence (which differs from the often ridiculed superrationality assumption in classic game theory) for the players to identify equilibrium strategies. The same argument might be used for intraperson games because the strategies of different selves vary greatly, and strong selection pressures push for the best possible outcomes of individual decision making. For example, someone who undertakes a suboptimal strategy of giving in to his or her desire for fat intake is unlikely to stay fit or to produce offspring with similar strategies. Similar thinking dominates the development of evolutionary psychology (Buss 1999; Tooby and Cosmides 1992).

According to the learning literature (Fudenberg and Levine 1998), a person's ability to adopt strategies that offer better welfare may occur with simple learning using basic intelligence (e.g., reflex), and therefore people may reach complicated equilibriums in the long run. For example, the simple best-response strategy in the familiar Cournot game (i.e., the player selects a strategy that is the best response to the observed history of previous periods) eventually leads to Nash equilibrium (Fudenberg and Levine 1998). This support is also consistent with psychology theories; for example, structure theory posits that the ego develops and learns through repeated actions over many years.

Therefore, these streams of research argue convincingly that at least some selves are capable of identifying better strategies and, over the long run, possibly even reaching equilibrium outcomes with little (or no) intelligence. In turn, I argue that it is appropriate to model individual decision making as an outcome of intraperson games.

Recently, economists have begun to model individual decisions explicitly by extending their conceptualizations beyond a singular preference structure. Fudenberg and Levine (2006) develop a model of a dual self (see also Bernheim and Rangel 2004), which consists of a long-term, patient self and a short-term, impulsive self. This approach represents a specific implementation of the TIG propose herein.

The TIG

The proposed TIG consists of two components: a new conceptual framework of multiple selves that is amenable to game theoretical modeling and a specific mathematical apparatus that allows the interactions of those selves to be modeled as games. After presenting the theory in this sequence, I offer a brief discussion of potential applications of the TIG in various disciplines.

A Conceptual Framework of Multiple Selves

Many different paradigms of multiple selves have been proposed in the literature, though virtually none of them define the relationships among the selves precisely enough to make the paradigm amenable to quantitative modeling. In response, I propose a new conceptual framework that is general enough to capture the essence of multiple selves without appearing partial to any particular theory; furthermore, it consists of precise characteristics for each self and the relationship among the selves. Thus, the proposed framework provides a general foundation on which different theorists may model individual decision making as intraperson games, consistent with their own paradigms of multiple selves. To provide intuitive links to existing literature, I discuss the TIG's relationship to structure theory and the society-of-minds theory when relevant.

The proposed framework can be summarized as follows: (1) Each unique entity within the mind is an agent, (2) all agents are classified into four different types, (3) agents within each type have the same characteristics, and (4) the nature of interactions among agents is determined by the types of these agents but is not agent specific. Whereas psychiatric theories tend not to treat action as a unique entity inside the mind, AI research considers both preference and action unique entities. Minsky (1986) calls all actions agents; for example, he considers the action of building blocks a build block agent. I follow this latter tradition and define all unique entities as agents in the new framework, which enables me to include all paradigms of multiple selves.

However, Minsky (1986) does not specify any specific relationships among agents, and though psychiatric theories distinguish among the id, ego, and superego, they do not specify precise relationships with regard to their interactions. Therefore, I synthesize existing literature to develop four distinctive types of agents with two different levels. When cast in the game theoretic framework, agents in the higher level are the players, and those in the lower level are the strategies that higher-level agents might use. Table 1 contrasts the various characteristics of these agents.

In the TIG, the two types of lower-level agents are referred to as behavioral and identity agents. Behavior agents are the actions a person might take, and they represent the entities inside the mind that are responsible for implementing specific actions. Psychiatric theory does not model such behavior agents formally but simply treats them as general action. Following the literature, I assert that behavior agents do not have utilities themselves and mirror the actions defined in the standard game theory.

Identity agents consist of the unique preferences of an individual person; in the structure theory paradigm, they would correspond to the drive derivatives of the id and the rules of the superego. Thus, the angel on one shoulder and the devil on the other refer to two contrasting identity agents. Other common folk wisdom, such as "enjoy life as if there were no tomorrow," also refers to a type of identity agent. Each identity agent has its own utility function and acquires utility if it is selected to represent the person's preference. Identity agents are not modeled in standard game theory, which assumes that each individual has a singular identity.

In the TIG, two types of higher-level agents are also defined: efficiency (control behavior) and equity (control identity) agents; this structure is based on literature in social

TABLE 1
Four Types of Agents in the TIG

	Higher-Level Agents		Lower-Level Agents	
	Efficiency Agents	**Equity Agents**	**Behavior Agents**	**Identity Agents**
Examples of agents of each type	Maximize the sum of utility from all identity agents	Choose each identity agent with a certain probability	Eat cake	Enjoy life as if there were no tomorrow
Role in TIG	Players	Players	Strategies/actions	Strategies/actions
Payoff	Overall utility of all identity agents	How utilities are distributed across identity agents	N.A.	Utility of individual identity agent
Strategies	Choose which behavior agents to play	Choose which identity agents to assume	N.A.	N.A.
Corresponding concept in structure theory	Ego	Ego	N.A.	Id and superego
Corresponding concept in society of mind	Higher-level agents	Higher-level agents	Agents	Agents
Corresponding concept in standard game theory	Players	N.A.	Actions	None (singular entity)

Notes: N.A = not applicable.

welfare, which notes the perpetual trade-off between efficiency and equity. From social planners' point of view, it is not enough to ensure efficient allocation (i.e., maximize social welfare according to the sum of utilities for all members in a society); some equitable division of that welfare must also occur among members of a society. Actual social policies themselves usually result from a compromise between the drive for greater efficiency and the drive for improved equity.[2]

If a person consists of multiple selves, he or she must also confront the trade-off between efficiency and equity to make decisions. That is, although individual decision making attempts to make the person better off overall (efficiency), people also consciously and unconsciously work to ensure that their selves take turns to dominate (equity), even if this means lower overall utility (e.g., a common and successful strategy in weight control is for a person to allow him- or herself to eat junk food one day each week).

In turn, efficiency agents are entities that make conscious choices regarding which behavior agent to use in a given situation and therefore correspond to the coping methods (decision rules) of the ego in structure theory. Because efficiency agents are interested in the overall utility of all identity agents, their objective is to maximize the sum of these utilities. Therefore, in the context of the TIG, efficiency agents represent the players, and behavior agents represent their strategies. Efficiency agents likely exist at the conscious level and are capable of sophisticated thinking, as assumed in standard game theory, which models them as players.

In contrast, equity agents select which of the identity agents to use and therefore correspond to other parts of the ego in structure theory. A familiar saying illustrates how equity agents work; namely, people "wear many different hats," and behavior changes depend on which hat (or identity) is being worn at a given time. In the TIG, hats are the identity agents, and equity agents select which identity agent (hat) a person wears in a particular situation, with or without conscious awareness. Unlike efficiency agents, equity agents attend to how utilities get distributed across different identity agents, so their payoff likely corresponds to whether every identity agent receives a fair chance of being selected. Equity agents also are players in the TIG, and their strategies are the identity agents; thus, their objective is to select a specific identity agent to represent the person at a given moment, such that in the long run, all relevant identities have a fair (though not necessarily equal) chance of selection. Although they likely function at both conscious and unconscious levels, equity agents may not be capable of sophisticated thinking. Furthermore, standard game theory does not include equity agents; in many cases, people treat their implications simply as irrational behavior.

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[2] For example, consider family decision making with two parents and multiple children. One parent's objective could be to ensure that the sum of utilities for all children is maximized, even if that means giving one child most of the resources and minimum amounts to the others. Another parent's objective could be to ensure that each child derives a minimum utility from the decision and that the maximum difference among all children does not exceed a ceiling level. Thus, family decisions are the result of discussion and compromise between the two parents.

Formal Specification of Intraperson Games

Building on the preceding conceptual framework, I specify the requisite mathematical apparatus for the TIG to make it amenable to game theoretical analysis. A normal (strategic) form game in standard multiperson game theory includes three elements (Fudenberg and Tirole 1991): a finite set of players, the pure strategy space for each player, and payoff functions for each combination of strategies. A mixed strategy represents a probability distribution over pure strategies and essentially randomizes several pure strategies. In line with classic (multiperson) game theory, intraperson games are defined in the normal form and suggest the corresponding TIG definitions for each element using appropriate mathematical formulations and supported by theoretical arguments. Finally, the equilibrium concept and its existence in TIG are discussed.

Definition 1: There are two types of players in TIG, efficiency agents and equity agents.

The pure strategies for efficiency agents are behavior agents (actions a person could take in a game), just as in standard game theory. The pure strategies for equity agents are the various identity agents from which they might choose, whether consciously or (more likely) unconsciously. In a given TIG, the pure strategy space of equity agents probably involves identity agents from both the superego and the id. (It is also possible that they are drive derivatives of the id.) Bénabou and Tirole (2004) take a similar approach by allowing individual decision makers to choose between a "no-willpower" option and a "willpower-dependent" option, which is equivalent to the equity agent selecting between two identity agents in TIG, though Bénabou and Tirole do not model the role of the efficiency agent explicitly.

Definition 2: The pure strategy for an efficiency agent is $S_b = \{s_b^1, \ldots, s_b^B\}$, or the set of all relevant behavior agents; the pure strategy for an equity agent is $S_i = \{s_i^1, \ldots, s_i^I\}$, or the set of all relevant identity agents.

A mixed strategy in multiperson game theory reflects a probability distribution over pure strategies, but in the TIG, the mixed strategy must be considered separately for efficiency and equity agents. For an efficiency agent, the mixed strategy is a straightforward randomized choice among the various possible pure strategies, just as it is in multiperson game theory. For an equity agent, mixed strategy means that an equity agent's choice of identity agents at a given time is not deterministic. Freud's (1923) original work (see Gay 1989), as well as more recent work (e.g., Brenner 1982), supports this assertion. Psychoanalytic theory states that the id and superego compete in any given decision-making situation, such that the drive derivatives of the id win on some occasions and the rules of the superego win on others. If a person always listens to his or her id drive derivatives, the anxiety and/or depressive effect from the superego becomes salient and diminishes the chances he or she will continue to listen to the id the next time. Conversely, if a person consistently listens to his or her superego, the displeasure from the id becomes salient and diminishes the chances of following the superego. Therefore, the selection of an identity agent on a given occasion is rarely deterministic; rather, the balance between defense (superego) and drive gratification (id) remains mobile (Brenner 1982). Note that there are exceptions to this statement; always succumbing to drive derivatives is the definition of clinical illness, and people who always follow their superego become rigid, obsessive, and/or compulsive. However, most people fall somewhere in between.

Definition 3: The mixed strategy for an efficiency agent is $\Sigma_b = \{\sigma_b^1, \ldots, \sigma_b^B\}$, a probability distribution over S_b; the mixed strategy for an equity agent is $\Sigma_i = \{\sigma_i^1, \ldots, \sigma_i^I\}$, a probability distribution over S_i.

The payoff for an efficiency agent parallels the Von Neumann–Morgenstern utility in its familiar form, whereas the payoff for an equity agent is more complex. As social welfare literature demonstrates, it is easy to define efficiency, but there is no consensus regarding what equity really implies. Therefore, instead of constraining the TIG by a specific formulation of equity agents, the payoff for an equity agent is loosely defined as a function of the utilities of each identity agent and the probabilities of each outcome. Applications of TIG can specify a specific formulation that is consistent with the problem at hand (as is done in the next section for variety-seeking behavior).

Definition 4: The payoffs for the four types of agents are as follows:

a. Behavior agents do not have a payoff.

b. The payoff for an identity agent m is 0 if the equity agent does not select it and $u^m(s_b^n)$ if the equity agent selects it and the efficiency agent's strategy is s_b^n.

c. The payoff for an efficiency agent is the sum of utilities of all identity agents, $u_b(\Sigma_b, \Sigma_i, u^m[s_b^n]) = \Sigma_{m=1}^{I}\Sigma_{n=1}^{B}\sigma_i^m\sigma_b^n u^m(s_b^n)$.

d. The payoff for an equity agent is a function of the payoffs for each identity agent and the probabilities that each outcome will be realized, $u_i(\Sigma_b, \Sigma_i, u^m[s_b^n]) = f(\Sigma_b, \Sigma_i, u^1[s_b^1], u^1[s_b^2], \ldots, u^1[s_b^B], u^2[s_b^1], \ldots, u^I[s_b^B])$.

To complete the specification of TIG, I address the equilibrium and process of reaching equilibrium. Many different equilibrium concepts (e.g., Nash, evolutionarily stable strategy) exist in the standard game theory, but I do not attempt to take a stand on which is most appropriate for the TIG. For the purposes of this article, I simply use the Nash equilibrium and derive the following claim from Nash's (1950) theorem, which states that any finite games expressed in normal form have at least one equilibrium (including mixed strategies):

Claim 1: There is at least one Nash equilibrium, which may involve mixed strategies, for the TIG.

The two types of players in the TIG, efficiency agents and equity agents, do not operate in similar ways. At the conscious level, the efficiency agents likely conduct sophisticated thinking and anticipate other players' strategies. In other words, they behave in a rational way that is consistent with standard game theory. At the unconscious level (for the most part), equity agents possess far less ability to think strategically. Without imposing a specific structure, I simply state that equity agents identify a better strategy through one of three mechanisms discussed in the literature.

Claim 2:

(a) An efficiency agent identifies its optimal strategy using strategic thinking, as assumed in standard game theory.

(b) An equity agent identities a better strategy following one of three mechanisms:

- (i) Strategic thinking, as assumed in standard game theory;
- (ii) Simple heuristics, as assumed in the learning theory of games; or
- (iii) Mutation and selection, as assumed in evolutionary game theory.

Applications of the TIG

Many disciplines could benefit from the TIG, including, but not limited to, psychology, medicine, AI, economics, and marketing. Table 2 provides a few examples within each discipline that might profit readily from the TIG. In marketing, for example, almost without exception, consumers are assumed to have a singular utility function and an objective of maximizing this utility. Instead, the TIG argues that the outcomes of individual decisions reflect compromises between efficiency agents (the only thing modeled in extant marketing literature) and equity agents (absent from extant marketing literature). This new perspective can shed light on how consumers make decisions about new product adoption; for example, a consumer may purchase a new product to satisfy one of his or her identity agents, even though the overall utility for this consumer decreases. It also can inform advertisers how to design their advertisements to target the interactions between efficiency and equity agents and thus influence consumers' acceptance of an advertising message. To illustrate the utility of the TIG, in the next section, I develop a parsimonious model for variety-seeking behavior, a familiar topic in marketing.

TABLE 2
Potential Applications of the TIG

Discipline	Examples of Potential Applications
Marketing	Variety seeking, new product adoption, advertising acceptance, pricing strategy, negotiation
Psychology	Cognitive psychology, personality psychology, developmental psychology
Medicine	Bipolar syndrome, placebo effect, phobia, suicide, weight loss, addiction
Economics	Consumer preference, choice theory
AI	Machine Intelligence

An Application of the TIG

Variety-seeking behavior, an important topic with a long tradition in marketing (e.g., Bass 1974; Bass, Pessemier, and Lehmann 1972; McAlister and Pessemier 1982; Ratner, Kahn, and Kahneman 1999), is driven by intrapersonal factors and uncertainty about preferences. Existing literature considers three types of intrapersonal factors: satiation (Coombs and Avrunin 1977; Lattin and McAlister 1985; McAlister 1982), stimulation (Berlyne 1970; Faison 1977), and hedging (Farquhar and Rao 1976; Huber and Reibstein 1979). Empirical observations also show that variety-seeking behavior often is stochastic in nature (Trivedi, Bass, and Rao 1994).

I illustrate the utilities of the TIG with a parsimonious TIG model developed for variety-seeking behavior and show that the model provides accurate predictions about whether an individual consumer will seek variety. The resultant theoretical insights offer guidelines to managers regarding what actions they can take to encourage or discourage variety seeking. I also discuss an empirical study designed to test the validity of the theoretical model.

Theoretical Model

To develop a specific TIG model for variety seeking, I make a few assumptions about aspects that the general TIG does not specify, based on existing knowledge about variety seeking, specifically in terms of (1) the numbers of players and the number of strategies for each player, (2) the payoff for each player, (3) how an equity agent identifies a better strategy, and (4) the dynamic structure of the game and the sequence of moves. Variety-seeking behaviors are characterized by alternating choices between two or more options, such as the choice of a lunch entrée (tasty burger or healthy salad) or a drink (coffee, juice, or water). Although existing variety-seeking literature often includes many options, to obtain a precise test of the TIG, I focus on a choice situation with only two options. In most such cases, a person experiences conflict between two identity agents; for example, in the lunch choice, the consumer must choose between the desire for fat (Identity Agent A) and the desire for health (Identity Agent B).

Assumption 1: An efficiency agent has two pure strategies $S_b = \{s_b^1, s_b^2\}$, and an equity agent has two pure strategies $S_i = \{s_i^1, s_i^2\}$. The mixed strategy of the efficiency agent is $\{\sigma_b, 1 - \sigma_b\}$, and the mixed strategy of the equity agent is $\{\sigma_i, 1 - \sigma_i\}$.

The payoffs for identity and efficiency agents are as they are defined in the general TIG, though it only defines the equity agent's payoff broadly. Therefore, I make a specific assumption about the payoff for equity agents in a variety-seeking context.

Empirical literature on variety seeking demonstrates that the decision depends on how often each option has been chosen in the past and suggests a U-shaped relationship (Ratner, Kahn, and Kahneman 1999). Therefore, equity agents change their strategy on the basis of how often each identity agent has been chosen, probably not on how much utility each identity agent would achieve if selected, similar to psychiatric theories pertaining to conflict management. In his influential book *The Mind in Conflict*, Brenner (1982) claims that whether a drive derivative or a superego rule dominates at a given time depends on how often each has been satisfied previously. Thus, I propose the following utility formulation for equity agents in a variety-seeking context:

Assumption 2: Payoffs in the variety-seeking context are as follows:

a. The payoff for an identity agent m is 0 if the equity agent does not selected it and $u^m(s_b^n)$ (hereinafter abbreviated as u^{mn}) if the equity agent selects it and the efficiency agent's strategy is s_b^n.

b. The payoff for an efficiency agent is the sum of expected utilities of the two identity agents,

$$\text{(1)} \quad u_b(\sigma_b, \sigma_i, u^{11}, u^{12}, u^{21}, u^{22}) \\ = \sigma_b \sigma_i u^{11} + \sigma_b(1-\sigma_i)u^{21} \\ + (1-\sigma_b)\sigma_i u^{12} \\ + (1-\sigma_b)(1-\sigma_i)u^{22}.$$

c. The payoff for an equity agent is

$$u_i(\sigma_b, \sigma_i) = f(\sigma_b, \sigma_i) \text{ and}$$

$$\frac{\partial^2 u_i(\sigma_b, \sigma_i)}{\partial \sigma_i{}^2} < 0.$$

Specifically, a quadratic formulation is assumed[3]:

$$\text{(2)} \qquad u_i(\sigma_b, \sigma_i) = -(\sigma_i - q\sigma_b - p)^2 + c.$$

Quadratic formulation has a long tradition of being used in marketing literature (Lilien, Kotler, and Moorthy 1992). The foregoing quadratic formulation allows an equity agent to have an interior optimal mixed strategy (σ_i between 0 and 1), but it does not eliminate the boundary solution (σ_i equals either 0 or 1). In this specific case, "interior optimal" means that the equity agent prefers that both identity agents gain some utility. Parameters p and q are coefficients associated with a quadratic formulation, and c is a constant independent of σ_i. In this specific case, p is related to the base utility an equity agent will receive if the same identity agent and behavioral agent are always selected ($\sigma_i = 0$, and $\sigma_b = 0$), and q is related to the magnitude of the effect that the efficiency agent's strategy (σ_b) will have on the equity agent's utility.

The general TIG suggests three possible mechanisms that an equity agent could adopt to identify a better strategy. Given the specific context of variety seeking, the equity agent is likely to use heuristics (i.e., learning theory) to determine its strategy. Specifically, I propose that the equity agent will use the best-response heuristic, one of three widely used dynamic adjustment processes in the learning literature pertaining to game theory (Fudenberg and Levine 1998), in which a player selects a strategy (action) that represents the best response to the observed history of previous periods. The best-response adjustment dynamics are particularly suitable to model the equity agent in the variety-seeking context for two reasons: First, it captures the notion that variety seeking is mostly a non-zero-order process, and it allows history to affect the current-stage decision in the model.[4] Second, it reflects the notion that the choice of identity agents in variety-seeking contexts is not likely to be highly involved, and the equity agent may not be able to anticipate the efficiency agent's strategy.

Assumption 3: The equity agent determines its strategy on the basis of the best-response adjustment.

Because variety seeking, by definition, refers to choice behavior that begins in youth and repeats until a person dies, it is logical to study the problem in a finitely repeated game framework. Thus:

Assumption 4: The efficiency agent and the equity agent move simultaneously in each stage, and the game is repeated over a finite horizon.

The subgame perfect outcome for a finitely repeated game coincides with the equilibrium in its stage game if the stage game equilibrium is unique, as is the case for this game. The key theoretical result is presented as Theorem 1:

Theorem 1: A consumer seeks variety between two behavior agents if and only if p is bounded between B_1 and B_2; the probability of selecting Behavior Agent 1 is

$$\text{(3)} \qquad \sigma_b^* = \frac{u^{22} - u^{21} + q(u^{22} - u^{12}) - p\Delta}{2q\Delta},$$

where

$$\Delta = u^{11} - u^{21} - u^{12} + u^{22},$$

$$B_1 = \left(\frac{u^{22} - u^{12}}{\Delta} - 2\right)q + \frac{u^{22} - u^{21}}{\Delta},$$

and

$$B_2 = \left(\frac{u^{22} - u^{12}}{\Delta}\right)q + \frac{u^{22} - u^{21}}{\Delta}.$$

The probability of selecting Identity Agent 1 is

$$\text{(4)} \qquad \sigma_i^* = p + q\sigma_b',$$

where σ_b' is the observed probability of selecting Behavior Agent 1 in the previous history, where history is defined as the previous n periods that the agents remember (or about which they care). Thus, $\sigma_b' \to \sigma_b^*$ as the number of repetitions approaches n (note that n is likely to be individual specific). (For a proof, see the Appendix.)

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[3] Other specific formulations are possible; the purpose here is to propose a parsimonious model that can capture variety-seeking dynamics.

[4] I thank an anonymous reviewer for pointing out this important aspect of variety seeking.

The intuition behind the equilibrium for the variety-seeking game is as follows: Although the equity agent follows the best-response adjustment (Equation 4), the efficiency agent anticipates this strategy. If the efficiency agent consistently plays its equilibrium strategy (Equation 3), regardless of the equity agent's actions, the game converges to equilibrium quickly after some repetitions (as $\sigma_b' \to \sigma_b^*$).

Theorem 1 also specifies the conditions in which a person will seek variety; such an insight is not possible with existing qualitative theories. It further provides a coherent theoretical explanation for variety seeking due to intraperson factors.[5]

An Empirical Study

To test the validity of this model and, more important, to offer empirical support for the TIG, I conducted a small empirical study to determine whether the conditions specified in Theorem 1 are robust for predicting whether a person actually seeks variety, which differs from prior research that has attempted to predict variety-seeking choice on the basis of choice history. A good predictive performance supports the notion that variety seeking may be explained by the interactions of multiple selves within each person.

Two variety-seeking cases were selected on the basis of interviews with students at a major U.S. university; two identity agents exist in each case, and the decisions normally involve a choice between two types of behavior. The first case is what to eat for lunch, which appears to consist of two identity agents (eating something healthy versus something that tastes good) and two major behavior agents (salad versus burger). The second case pertains to the choice of a video to watch, in which case two key identity agents (have fun and relax versus be emotionally uplifting and rewarding) and two behavior agents (comedy/action videos versus emotionally involving videos) again inform the choice.

For each case, the participants were asked to respond to seven questions. The first six questions are used to obtain the six parameters that specify the variety-seeking condition in Theorem 1. The four different payoffs (u^{mn}) are obtained by direct rating questions (e.g., "Rate your enjoyment of having salad when you are in the mood of giving your body healthy food"). The parameters p and q are obtained on the basis of the optimal strategy of the equity agent (Equation 4). Participants were asked to indicate for a given observed σ_b (e.g., "if you had been eating salad 6 out of 7 times during the last week") how likely (σ_I) they would be in a given mood (e.g., "in the mood to give your body healthy food"). Each participant was asked twice, for different values of σ_b. Note that these questions are purely hypothetical and ask participants how likely it is that they would be in a specific mood, not whether they would make a certain choice. Their answers do not indicate their actual behavioral one way or the other.[6] Finally, the two pairs of (σ_b, σ_I) are substituted into Equation 4, which is solved for p and q.

In the final question, on the basis of their real-life behavior during the previous three months, participants were asked whether they always stuck to the same option (i.e., non–variety seeking) or sometimes picked one option and, at other times, picked the other (variety seeking). The responses to this question were used to represent actual behavior, against which the model's predictions were compared. The objective was to test how well this stated real-life behavior could be predicted using the six parameters and Theorem 1.

For each case, each respondent was evaluated for whether his or her parameter values indicated that he or she satisfied the variety-seeking conditions in Theorem 1. These predicted behaviors were then compared with respondents' self-stated, real-life behaviors. The 61 valid responses for food and 57 for videos appear in Table 3, Panels A and B, respectively. For food choice, 39 participants indicated that they sought variety; the model predicted that 42 participants would, and 32 of these were participants who indeed sought variety (chi-square test, $p = .003$). For video choice, 36 participants indicated that they sought variety; the model predicted that 30 participants would, and 22 of these were participants who indeed sought variety (chi-square test, $p = .093$).

Managerial Implications

These empirical results provide some evidence that the parsimonious TIG model is robust and captures the dynamics of variety-seeking behavior. This new understanding has several important managerial implications. A firm launching a new product into a market (or a firm with a small market share) might want to encourage more variety-seeking behavior, whereas a dominant firm would probably want to discourage it. Firms also may want to turn variety-seeking consumers into loyal consumers if possible.

With the new framework based on the TIG, which indicates which individual consumers are likely to seek variety, managers have more specific guidelines regarding how to influence consumers' choice behavior. According to Theorem 1, these firms should examine the six parameters (u^{mn}, p, and q) and design specific marketing tools to influence one or more of these parameters, such that more (fewer) consumers in the target segment fall within (outside) the variety-seeking region specified in Theorem 1.

Summary and Discussion

This article presents a quantitative framework (the TIG) for studying individual decision making that builds on qualitative theories used across disciplines, all of which posit that

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[5] A more extensive analysis of Theorem 1 reveals that it can provide theoretical explanations for the three mechanisms suggested in behavioral literature for intrapersonal variety seeking—namely, satiation, stimulation, and hedging. This analysis is available on request.

[6] This response does not necessarily indicate variety seeking. Almost all participants stated that their probabilities are other than 0 or 1 (with the exception of one participant in the food-choice task and two participants in the video task). Nevertheless, only 64% and 63% of participants stated that they sought variety in food and video during the previous three months, respectively.

TABLE 3
Predicting Variety Seeking

A. Food Choice

		Predicted by Theorem 1		
		Variety Seeking	Non–Variety Seeking	Total
Stated by participant	Variety seeking	32	7	39
	Non–variety seeking	10	12	22
	Total	42	19	61

B. Video Choice

		Predicted by Theorem 1		
		Variety Seeking	Non–Variety Seeking	Total
Stated by participant	Variety seeking	22	14	36
	Non–variety seeking	8	13	21
	Total	30	27	57

(1) there are multiple selves within each person and (2) individual decisions are the result of the interaction among these various selves. The new TIG has two components. The first is a conceptual framework of multiple selves, which is categorized into four different agent types. All identified agent types have well-defined characteristics and are amenable to quantitative modeling. The second component is a specific mathematical apparatus, based on the conceptual framework, that makes it possible to build models for intraperson games.

The advantages of the TIG lie in its ability to capture individual decision-making processes in a more realistic framework with a rigorous apparatus. It also enables researchers to study decision problems that previously have been studied only in conceptual frameworks and qualitative theories. Therefore, the quantitative nature of this theory makes it feasible to investigate complex problems and provide precise insights.

To demonstrate the utility of the TIG, a parsimonious TIG model for variety-seeking behavior was developed, and it was shown that stochastic variety-seeking behavior can be explained as a mixed-strategy equilibrium in the TIG. The model provides precise conditions in which an individual consumer will seek variety. When this insight was tested with an empirical study of two variety-seeking cases (lunch choice and video choice), the empirical results supported the notion that the parsimonious TIG model captures the dynamics behind variety-seeking behavior and offers useful guidelines to managers who are interested in changing the scope of variety-seeking behavior among their target consumers.

Many promising areas for further research remain. A fruitful direction pertains to the equilibrium in TIG. It would be helpful to investigate which equilibrium concepts are most appropriate for the TIG and, if necessary, to develop a new equilibrium concept that is most appropriate for single-person decision making. In addition, research should explore cooperative games within the TIG. Whereas a noncooperative game framework is adopted here, it would be worthwhile to study the TIG from a cooperative game theoretical perspective. This approach may require some additional assumptions about how different agents reach an equilibrium (related to Claim 2), but otherwise, the current TIG would remain relevant. I also hope that this new theory will lend itself to various marketing-relevant applications that can shed new light on consumer decision making.

Appendix
Proofs

Lemma A1

The efficiency agent's expected utility in Stage Game G is strictly convex over σ_b if $q\Delta > 0$ and is strictly concave if $q\Delta < 0$, and the extreme value point is located at

$$\sigma_b'' = \frac{u^{22} - u^{21} + q(u^{22} - u^{12}) - p\Delta}{2q\Delta}. \tag{A1}$$

The function is monotonic if $q\Delta = 0$, where

$$\Delta = u^{11} - u^{21} - u^{12} + u^{22}. \tag{A2}$$

Proof

The equity agent's utility is defined in Equation 2. Because it follows best-response dynamics and bases its strategy on the efficiency agent's aggregate actions in previous stages, the equity agent's optimal strategy is simply (setting the first derivative to 0):

$$\sigma_i^* = p + q\sigma_b. \tag{A3}$$

The efficient agent's utility is

$$\begin{aligned} u_b(\sigma_b, \sigma_i, u^{11}, u^{12}, u^{21}, u^{22}) &= \sigma_b\sigma_i u^{11} \\ &+ \sigma_b(1 - \sigma_i)u^{21} + (1 - \sigma_b)\sigma_i u^{12} + (1 - \sigma_b)(1 - \sigma_i)u^{22}, \end{aligned} \tag{A4}$$

and its objective is $\max_{\sigma_b} u_b$. Because the efficiency agent is capable of anticipating the equity agent's behavior, the equity agent's optimal strategy can be substituted into the efficiency agent's utility, and derivatives can be taken:

$$\frac{\partial u_b}{\partial \sigma_b} = -u^{22} + u^{21} - q(u^{22} - u^{12}) + (p + 2q\sigma_b)\Delta, \text{ and}$$

$$\frac{\partial^2 u_b}{\partial {\sigma_b}^2} = 2q\Delta,$$

such that

$$\frac{\partial u_b}{\partial \sigma''_b} = 0 \text{ implies that } \sigma''_b = \frac{u^{22} - u^{21} + q(u^{22} - u^{12}) - p\Delta}{2q\Delta}.$$

If $q\Delta > 0$, the utility is strictly convex, and there is no interior optimal and, thus, no variety seeking. If $q\Delta = 0$, the utility is monotonic, and again, there is no interior optimal. Thus, I focus on the case of $q\Delta < 0$, for which there could be an interior optimal (and variety seeking). Q.E.D.

Theorem A1 (Theorem 1) Proof

Following Lemma A1, if $q\Delta < 0$, the objective function is concave, and it is necessary to check where the extreme value point is located. It should be clear that $\sigma^*_b = \sigma''_b$ if $\sigma''_b \in (0, 1)$. In this case, Options 1 and 2 are chosen on the basis of the optimal probability σ''_b (mixed strategy). When $\sigma^*_b = 0$, if $\sigma''_b \leq 0$, Option 2 is always selected. When $\sigma^*_b = 1$, if $\sigma''_b \geq 1$, Option 1 is always selected. Because the equilibrium is unique in the stage game in all conditions, the equilibrium is the unique subgame perfect outcome for the entire (finitely repeated) game. It can also be shown that

$$\text{(A5)} \qquad \sigma''_b = 0 \text{ is equivalent to } p = \frac{u^{22} - u^{12}}{\Delta} q + \frac{u^{22} - u^{21}}{\Delta}$$

and

$$\text{(A6)} \quad \sigma''_b = 1 \text{ is equivalent to } p = \left(\frac{u^{22} - u^{12}}{\Delta} - 2\right) q + \frac{u^{22} - u^{21}}{\Delta}.$$

When the optimal strategy for the efficiency agent is a mixed strategy, the equity agent responds with $\sigma^*_1 = p + q\sigma'_b$, where σ'_b is the observed probability of the efficiency agent selecting Behavior Agent 1 in the previous history. Because the efficiency agent is capable of anticipating the equity agent's strategy, the efficiency agent can ensure that the game quickly converges to equilibrium by consistently playing its equilibrium strategy, which in turn leads the equity agent to converge to its own equilibrium strategy $\sigma^*_1 = p + q\sigma^*_b$. Q.E.D.

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Gabriel J. Biehal & Daniel A. Sheinin

The Influence of Corporate Messages on the Product Portfolio

The authors examine factors that change the influence of corporate messages for forming judgments about products in the company's portfolio (i.e., transfer). Corporate messages transferred more than a product message onto other products in the company's portfolio. However, a product message had more influence than corporate messages for that product. Moreover, a corporate ability (quality) message transferred more to the portfolio than did a corporate social responsibility message. Finally, a competitive product message that preceded a company product message and was positioned similarly to a company product lessened corporate message diagnosticity, reducing transfer. However, this occurred only for a product in the same category but not for a product in a different one. The authors discuss the implications of these findings for corporate brand and product brand managers and suggest directions for further research.

Although corporate messages can create an image that encompasses many aspects of the company (Drumwright 1996; Johnson and Zinkhan 1990), they may also transfer to consumers' judgments about the products the company markets (Duncan and Moriarty 1998; Gurhan-Canli and Batra 2004; Hatch and Schultz 2001; Raju and Dhar 1999). In this article, the term "transfer" refers to the influence of corporate messages on product beliefs and attitudes. Corporate messages transfer to product characteristics (Brown and Dacin 1997), price perceptions (Creyer and Ross 1996), perceived product values and evaluations (Goldberg and Hartwick 1990), brand beliefs and attitudes (Sheinin and Biehal 1999), product purchase intentions (Sen and Bhattacharya 2001), and product choices (Creyer and Ross 1996).

These studies establish corporate transfer to a single product but not to multiple products in a company's portfolio. Companies such as Toyota, 3M, and DuPont market portfolios of products across many categories while sending corporate messages to customer targets. For example, Toyota's "Made in the USA" corporate message communicates the company's commitment to domestic manufacturing. Toyota's corporate brand and product managers need to know which products will be influenced by the corporate message and whether all products will be influenced similarly. They also need to know whether corporate messages compared with single-product messages add value to a portfolio. Managers should not infer that corporate transfer to one product will generalize for several products, because products differ in many ways; for example, some products may be clearly differentiated from competitors, whereas others may not be. This may differentially influence the nature and extent of corporate transfer. In summary, a single product may be representative of a corporate positioning and therefore influenced by it. However, when the processing context becomes more complex, as in a multiproduct portfolio, corporate transfer across the portfolio is less obvious. We are unaware of any research that examines how changes in the corporate-message-processing context influence multiple product judgments.

Such changes are the focus of this research. In Study 1, we examine differences in corporate message content. In doing so, we extend the work of Brown and Dacin (1997), who find that corporate social responsibility (CSR) and corporate ability (CA) associations influence evaluations of a single product but through qualitatively different processes. In Study 1, we examine the effect of corporate message content on transfer and test whether Brown and Dacin's finding applies to multiple products. The study also compares corporate and product messages and explicitly measures the belief and attitudinal bases of corporate transfer. In Study 2, we examine the effect of changes in a product's competitive environment on corporate transfer. Competitive messages have been found to have a consistently negative impact on consumers' product information processing (Burke and Srull 1988; Keller 1987; Kent and Allen 1994), but their impact on corporate transfer is not understood.

Therefore, both studies investigate corporate transfer to multiple products in a company's portfolio in a more complex message-processing context than previous research. To develop hypotheses and interpret the results, we use the accessibility–diagnosticity framework (Feldman and Lynch 1988). This framework proposes that the probability that a

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piece of information is used to make a judgment reflects its (1) accessibility, or the ease with which it can be retrieved from memory; (2) diagnosticity, or the ability to make the judgment based on that information alone; and (3) accessibility and diagnosticity relative to other information. When consumers have several diagnostic information sources, selecting and using one lessens the use of others (Lynch, Marmorstein, and Weigold 1988). Thus, for corporate messages to influence products, they must be accessible when consumers think about product information, diagnostic in evaluating the product, and more accessible and diagnostic relative to other product information sources. In both studies, we vary the relative diagnosticity of corporate messages for making judgments about products in a portfolio. Study 1 examines the differential diagnosticity of different types of corporate messages and of corporate versus product messages. Study 2 varies the competitive message environment and traces its impact on corporate message diagnosticity for judging products in the company's portfolio. In the next section, we describe the theory and results of Study 1. Then, we present the theory and results of Study 2. We conclude with theoretical and managerial implications and suggestions for further research.

Study 1

Theoretical Framework

The diagnosticity of corporate versus product messages. Consider a company that uses a corporate message to position the corporate brand. The company also communicates messages for several products in its portfolio, but for simplicity, we consider just two, Products A and B. We make three assumptions. First, we assume that Products A and B are in unrelated product categories. Second, we assume that the company employs a "branded-house" strategy (Aaker and Joachimsthaler 2000), such that messages for Products A and B contain corporate retrieval cues (e.g., the corporate name or logo). Third, we assume that consumers encounter the corporate message before the product messages, thus establishing an accessible corporate memory trace before they evaluate the company's products.

When consumers evaluate a product, they search accessible knowledge in memory for diagnostic information about it (Lynch, Marmorstein, and Weigold 1988). According to the accessibility–diagnosticity framework, consumers use this knowledge in conjunction with externally available information to make judgments (Lynch and Srull 1982). In a portfolio context, potentially diagnostic knowledge includes corporate messages and product messages linked with the corporate name. Therefore, consumers have several accessible inputs when they evaluate Product A (i.e., corporate, Product A, and Product B messages).

How do consumers choose from multiple information sources? Consumers are "cognitive misers"; they use just enough information to solve the task and do not consider all accessible and diagnostic knowledge sources because information search is costly (Fiske and Taylor 1991). Furthermore, Feldman and Lynch (1988) propose that when two or more inputs are available, increasing the diagnosticity of one relative to the others lessens the use of the others (Lynch, Marmorstein, and Weigold 1987). An important influence of relative diagnosticity is the number of overlapping associations between two concepts (i.e., the extent to which they contain shared knowledge). Research shows that more overlapping associations enhance knowledge transfer between concepts by increasing the relative accessibility and diagnosticity of one when evaluating the other (Ahluwalia and Gurhan-Canli 2000; Keller 1987). Therefore, because Product B is in an unrelated product category (i.e., shares few associations), it is unlikely to be diagnostic for evaluating Product A. However, in a branded-house context, knowledge formed from the corporate message should have overlapping associations with Product A's messages and contain beliefs that are diagnostic for evaluating Product A (Brown and Dacin 1997; Keller 1987). Thus, corporate message associations should be more accessible and diagnostic in evaluating Product A than those of Product B and should be used to a greater extent. Conversely, Product B's messages should be more diagnostic than the corporate message in evaluating Product B—high message overlap is likely between Product B messages and existing Product B knowledge—but not for other, unrelated products in the portfolio, for which overlap is low. Thus:

- H_{1a}: A corporate message is more diagnostic than a product message for forming judgments about other products in the portfolio.
- H_{1b}: A product message is more diagnostic than a corporate message for forming judgments about the product.

The diagnosticity of CA versus CSR messages. Corporate ability messages are positioned on product-relevant dimensions, such as quality and service orientation. Corporate social responsibility messages are positioned on less-product-relevant dimensions, such as social responsibility and ethical orientation (Brown and Dacin 1997; Sen and Bhattacharya 2001). Both CA and CSR messages are diagnostic for judging products insofar as consumers use them to infer unknown product characteristics (Brown and Dacin 1997), though the effect on purchase intentions may be moderated by support for the CSR domain (Sen and Bhattacharya 2001).

Corporate ability messages should be more diagnostic than CSR messages for forming product beliefs. Consumers make inferences when evaluating products (Broniarczyk and Alba 1994; Dick, Chakravarti, and Biehal 1990), but it should be more difficult for them to infer product performance from CSR than from CA messages because the former are less correlated with product attributes. For example, Brown and Dacin (1997) find that CSR is unrelated to product attribute associations and evaluations, though it is related to corporate evaluation and, thus, product evaluation. Because CSR messages are not strongly associated with product attributes, corporate transfer should be relatively lower (Ahluwalia and Gurhan-Canli 2000).

Conversely, CA messages, which are positioned on product-relevant attributes, should be more diagnostic for forming product beliefs than should CSR messages. A company's quality associations should be strongly linked in consumers' minds with beliefs about product quality, making the former more diagnostic for evaluating them. In addition, consumers can use quality associations to infer performance on other attributes. Brown and Dacin's (1997) findings support this reasoning; that is, CA associations influence both corporate evaluation and product sophistication, and in turn, both influence product evaluations, though the sophistication relationship is stronger. Brown and Dacin conclude (p. 80) that "a reputation based on a company's abilities may have a greater impact on both specific product attribute perceptions and the overall corporate evaluation than a reputation for social responsibility." Therefore, we predict the following:

> H_2: CA messages are more diagnostic for forming product beliefs across the portfolio than are CSR messages.

Method

Design, stimuli, and message manipulations. Study 1 is a single-factor between-subjects design with four message levels (CSR, CA, product, and control). We communicated messages with carefully designed advertisements. We conducted two pretests. In the first (n = 42), participants evaluated potential product categories, and in the second (n = 30), they evaluated potential corporate names and identified product category attributes. On the basis of these pretests, we designed four full-page advertisements for a hypothetical financial services company (branded Atlantic Finance Company). Each advertisement had identical execution and element locations; listed from top to bottom, these are corporate name and logo, headline, message copy, common copy, and corporate name and logo again (see Appendix A). The purpose of the common copy was to establish a control condition against which we could measure the relative contribution of each message. The only difference among the advertisements was the message copy.

The CSR message described the company in terms of its ethical conduct, employee integrity, and charity and community efforts. The CA message described the company in terms of its customer service and quality. The product message described the company's Visa credit card in terms of convenience, ATM usage, and branded alliances. Each of these three messages had a similar word count. Finally, the control message contained only the common copy, which provided additional information about the credit card product. Guided again by pretests, we defined a three-product portfolio that consisted of a Visa credit card, insurance, and financial planners. Participants never received any attribute-specific information about insurance and financial planners.

Participants and procedure. Undergraduate students (n = 173) at a mid-Atlantic university participated in exchange for extra course credit. They were randomly assigned to conditions and were tested in groups of approximately 20. A booklet described the purpose of the experiment and contained the measures.

Participants first read that the study was about evaluating advertisements and products and then read that they would see an advertisement in test marketing. The experimenter used an overhead projector to expose participants for a set time to one of the four advertisements and asked them to look at them carefully ("much as you would if the advertisement interested you"). Next, participants completed company attitude measures. Then, they completed beliefs and attitude measures for each of the three products in the company's portfolio. Product beliefs were presented in two random orders. Next, participants completed potential covariate measures of category familiarity, knowledge, usage, and corporate name awareness and knowledge (order and covariate effects were not significant). Finally, participants gave demographic information and guessed the purpose of the research (none were correct).

Measures. The key measures were Visa credit card, insurance, and financial-planner beliefs and attitudes. We also used a measure of Atlantic Finance Company attitude to examine a competing explanation of the results. The seven-point belief scales had "likely/unlikely" endpoints, which we randomly reversed. Appendix B contains measurement items and reliabilities (each $\alpha > .78$).

Results

The diagnosticity of corporate versus product messages. H_{1a} predicts that a corporate message will be more diagnostic than a product message for forming judgments about other products in the portfolio. Recall that insurance and financial planners are the other products. Support for the hypothesis requires that corporate messages, pooled both across corporate condition and by condition, lead to higher beliefs and more positive attitudes for the insurance and financial-planner products than does a product message (for cell sizes, means, and standard deviations, see Table 1).

Consistent with H_{1a}, beliefs about other products in the portfolio (Table 1) were more positive when participants were exposed to a corporate message than to a product message. A 2 (message: corporate [CSR and CA pooled] and product) × 1 multivariate analysis of variance (MANOVA) with insurance and financial-planner beliefs and attitudes as dependent variables was significant ($F_{4, 135} = 5.42$, $p < .001$). The pooled beliefs were higher after a corporate message (M = 5.08) than after a product message (M = 4.48; $t_{139} = 3.65$, $p < .001$), and the pooled attitudes were more positive (M = 4.62 versus M = 3.84; $t_{139} = 4.26$, $p < .0001$).

For insurance, a 2 (message: corporate and product) × 1 MANOVA with insurance beliefs and attitudes as dependent variables was significant ($F_{2, 138} = 10.71$, $p < .0001$). Beliefs about insurance were higher after a corporate message (M = 4.73) than a product message (M = 4.08; $t_{140} = 3.28$, $p < .01$). By corporate condition, the difference was directional only after the CSR message (M = 4.41; $t_{90} = 1.49$, $p < .15$) and significant only after the CA message (M = 5.06; $t_{88} = 4.27$, $p < .0001$). As further confirmation, insurance beliefs were higher after a corporate message than after the control (M = 3.76; $t_{130} = 4.16$, $p < .0001$), but after a product message, they did not differ ($p > .30$). By condition, both were higher (CSR: M = 4.41; $t_{80} = 2.47$, $p < .05$; CA: M = 5.06; $t_{78} = 4.73$, $p < .0001$). We replicated all preceding belief results for attitude, except that the CSR (M = 4.41) versus product message (M = 3.73) comparison was also significant ($t_{90} = 3.15$, $p < .01$).

For financial planners, a 2 (message: corporate and product) × 1 MANOVA with financial-planner beliefs and attitudes as dependent variables was significant ($F_{2, 137}$ =

TABLE 1
Study 1: Means and Standard Deviations by Condition

Measure by Product	CSR Message (n = 52)	CA Message (n = 50)	Product Message (n = 40)	Control (n = 31)
Beliefs				
Insurance	4.41	5.06	4.08	3.76
	(.92)	(.98)	(1.17)	(1.47)
Financial planner	5.26	5.60	4.87	4.72
	(.96)	(1.01)	(.94)	(1.29)
Visa credit card	4.05	4.16	5.86	3.90
	(.91)	(1.13)	(.83)	(1.04)
Attitudes				
Insurance	4.41	4.71	3.73	3.98
	(1.09)	(.97)	(.95)	(1.16)
Financial planner	4.61	4.76	3.96	4.10
	(1.10)	(1.15)	(1.24)	(1.22)
Visa credit card	4.29	4.56	5.34	4.45
	(1.14)	(1.20)	(1.05)	(1.32)

6.97, $p < .01$). Beliefs about financial planners were higher after a corporate message (M = 5.43) than after a product message (M = 4.87; $t_{139} = 3.06$, $p < .01$). By corporate condition, the difference was significant after both the CSR and the CA messages (CSR: M = 5.26; $t_{89} = 1.96$, $p < .05$; CA: M = 5.60; $t_{88} = 3.52$, $p < .001$). As further confirmation, after a corporate message, financial-planner beliefs were higher than the control (M = 4.72; $t_{129} = 3.21$, $p < .001$), but after a product message, they did not differ ($p > .50$). By condition, both were higher (CSR: M = 5.26; $t_{79} = 2.17$, $p < .05$; CA: M = 5.60; $t_{78} = 3.41$, $p < .001$). We replicated all preceding belief results for attitude.

H_{1b} predicts that product messages will be more diagnostic than a corporate message for forming judgments about the product. Support for this hypothesis requires that credit card beliefs and attitudes are higher with the product message than with the corporate messages. Consistent with H_{1b}, a 2 (message: corporate and product) × 1 MANOVA with Visa credit card beliefs and attitudes as dependent variables was significant ($F_{2, 138} = 49.28$, $p < .0001$). Credit card beliefs were higher after a product message (M = 5.86) than after a corporate message (M = 4.11; $t_{140} = 9.61$, $p < .0001$). As further confirmation, after a product message, credit card beliefs were higher than the control (M = 3.90; $t_{68} = 8.68$, $p < .0001$), but after a corporate message, they did not differ ($p > .40$).

The beliefs we discussed previously stemmed directly from the product message and were unique to the product. Therefore, these results may reflect method bias; because the beliefs sourced directly from the product message, they should be higher after a product message than after a corporate message. To bolster the analysis, we also examined beliefs about four attributes that were common across all three products (e.g., "[Product] offers good customer service," "[Product] offers high quality"). If we find the same results for inferential beliefs that did not source directly from the product message, this would strengthen support for H_{1b}. Factor analyses of the common belief measures led to reliable scales for each product (each $\alpha > .83$). The results using common beliefs replicate those reported for unique beliefs and support H_{1b}. Finally, we replicated all belief results for credit card attitudes.[1]

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[1] An alternative explanation for these results is that they do not reflect corporate transfer but rather product-to-product "spillover" from the credit card to the two other products. Thus, lower evaluations arose because the two other products were perceived as fitting poorly with the credit card product, which was described in copy that was common to all conditions. Poor fit has been associated with brand devaluation (Aaker and Keller 1990). Although we had no fit measures to test this possibility directly, we ran regressions to measure the influence of Visa credit card attitudes on attitudes toward the two other products. The first, a moderated mediation analysis, regressed Visa credit card attitude, dummy (1 = the pooled CSR and CA conditions, 2 = the product condition), and the Visa credit card attitude × dummy interaction on pooled insurance and financial-planner attitudes. The interaction coefficient was not significant ($p > .50$), indicating that the influence of Visa credit card attitude did not vary across the experimental conditions. Then, we regressed attitudes toward Visa credit card and Atlantic Finance Company on pooled insurance and financial-planner attitudes, for the pooled CSR and CA conditions and the product message condition. Both regressions were significant (for pooled CSR and CA, $F_{2, 96} = 43.38$, $p < .0001$; for the product condition, $F_{2, 37} = 4.56$, $p < .05$). Visa credit card attitude was not a significant predictor in any condition (each $p > .10$)—that is, there was no spillover from it—whereas the Atlantic Finance Company attitude was significant in both cases (for pooled CSR and CA, $t_{96} = 7.14$, $p < .0001$; for product, $t_{37} = 2.34$, $p < .05$). Moreover, a comparison of pooled insurance and financial-planner means between the product message and the control conditions showed that neither beliefs (M = 4.48 versus control M = 4.24, $p > .30$) nor attitudes (M = 3.84 versus control M = 4.04, $p > .40$) differed significantly. This finding is important because it indicates that there was no product spillover to other products in the company portfolio (i.e., the product message was not diagnostic in the evaluation of other products in the portfolio).

The diagnosticity of CA versus CSR messages. H_2 predicts that CA messages will be more diagnostic for forming product beliefs across the portfolio than will CSR messages. This hypothesis implies that beliefs pooled across all three products in the portfolio and for individual products would be higher for CA than for CSR messages. A 2 (corporate message: CSR versus CA) × 1 MANOVA of pooled Visa credit card, insurance, and financial-planner beliefs was significant ($F_{3, 97} = 4.01$, $p < .01$). Consistent with H_2, pooled beliefs were higher after the CA message (M = 4.94) than after the CSR message (M = 4.57; $t_{99} = 2.80$, $p < .01$). By condition, corporate messages differed for insurance ($M_{CA} = 5.06$ versus $M_{CSR} = 4.41$; $t_{100} = 3.44$, $p < .001$), differed directionally for financial planners ($M_{CA} = 5.60$ versus $M_{CSR} = 5.26$; $t_{99} = 1.71$, $p < .09$), and did not differ for the credit card ($p > .60$).

Some additional results validate these findings. First, pooled product beliefs formed from CA (M = 4.94; $t_{77} = 4.15$, $p < .0001$) and CSR (M = 4.57; $t_{78} = 2.41$, $p < .05$) messages were higher than were control beliefs (M = 4.14). This finding shows that the CA message was more diagnostic both absolutely versus the control and relatively versus the CSR message, which was diagnostic itself. Second, the pooled and individual product attitudes for the two types of corporate messages did not differ (*p*s > .15), However, pooled attitudes formed from the CA message were more positive (M = 4.68) than the control (M = 4.18; $t_{78} = 2.47$, $p < .05$), whereas those formed from the CSR message (M = 4.43) were not ($p > .20$).

Discussion

Study 1 found that corporate messages were more diagnostic than product messages for the evaluation of other products in the portfolio (H_{1a}), whereas product messages were not diagnostic. However, product messages were more diagnostic than corporate messages for the product in question (H_{1b}). In addition, there were qualitative differences in corporate messages: CA messages were more diagnostic for forming product beliefs than were CSR messages (H_2), but not for attitudes. Moreover, comparisons with the control group showed that both CSR and CA messages were diagnostic for forming other product beliefs. This finding is important because it shows that the differential effect of CA versus CSR messages does not depend on a comparison to a nondiagnostic baseline message. However, there were no corporate message differences for the credit card product. This finding suggests that the common product information in each message is more diagnostic than corporate information for forming credit card evaluations. Finally, only the CA message led to a more positive attitude than the control across the portfolio, and additional analyses found no evidence of product-to-product spillover.

In summary, consistent with the accessibility–diagnosticity framework, Study 1 demonstrates that corporate messages can influence multiple products in a portfolio, whereas a product message shows no evidence of portfolio impact. Therefore, this study extends Brown and Dacin's (1997) findings by demonstrating the impact of qualitatively different corporate information on corporate message diagnosticity across an entire portfolio, not just a single product. We now examine the moderating effect of competitive messages on corporate transfer.

Study 2

Theoretical Framework

The diagnosticity of corporate versus competitive product messages. In practice, corporate messages appear in the presence of competitive product messages. Such messages may disrupt corporate transfer to the company's product portfolio. Research into competitive interference shows that competitive messages disrupt consumers' ability to retrieve and use product knowledge stored in memory. Competitive interference effects are robust and well documented. Keller (1987) finds that competitive interference reduced ad claim retrieval because of participants' confusion about which brand and which claims were associated with a particular advertisement. In a subsequent study, interference reduced cognitive response retrieval and ad evaluations, but this outcome was reversed by providing ad retrieval cues (Keller 1991). Kent and Allen (1994) find that competitive interference based on recall was lower for familiar than for unfamiliar brands. They argue that familiar brands have more distinctive memory traces than less familiar ones, which are grouped in consumers' minds under a general product category schema.

However, the adverse effects of competitive messages may extend beyond interference with product retrieval to consumers' inference making, an important aspect of information processing (Burke and Srull 1988). In particular, competitive messages may disrupt the inferential processes consumers use to relate concepts to one another. Such processes can have important evaluative implications. For example, corporate evaluations influence product judgments (Brown and Dacin 1997; Sheinin and Biehal 1999). As we argue subsequently, a competitive message may have an adverse impact if it is perceived as more diagnostic than a corporate message, thus reducing corporate transfer. Therefore, in a competitive message environment, an important consideration is which knowledge source, corporate or competitive, consumers perceive as more diagnostic when they evaluate a company's products.

A key consideration should be the sequence in which consumers encounter competitive and product messages. Different message sequences influence the disruptive nature of intervening information relative to a target (Burke and Srull 1988). We examine two sequences of four messages: corporate, the company's Product A, a direct competitor to Product A, and the company's Product B from a category that is unrelated to Product A. In both sequences, consumers always first encounter the corporate message. In a before-message sequence, the competitor-to-A message comes between the corporate message and Product A's message (corporate message → competitor-to-A message → Product A → Product B). In an after-message sequence, the competitor-to-A message comes after the corporate message and Product A's message (corporate message → Product A → competitor-to-A message → Product B). These sequences have different implications for the relative diagnosticity of the corporate versus the competitor-to-A product messages for evaluating Product A (i.e., corporate transfer).

In the before-message sequence, the competitor-to-A message should influence the diagnosticity of the corporate message to Product A, but such influence should be moderated by the positioning similarity between the competitor-to-A message and Product A. A lower-similarity positioning for a competitor-to-A message has few shared or overlapping associations with Product A, making it easy for consumers to distinguish it from Product A (Meyers-Levy and Tybout 1989; Sujan and Bettman 1989). Because lower-similarity competitor-to-A message knowledge is less accessible and diagnostic in processing Product A, other potentially accessible and diagnostic inputs are more likely to be used (Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988).

In the current context, the corporate message is the other input because Product B is in an unrelated product category and therefore is less diagnostic. Thus, we expect that consumers will use accessible corporate message knowledge that they integrate with the product message. The integrated representation will reflect corporate transfer and be accessible for subsequent product judgments. In summary, we expect that there will be little to no disruption of transfer when a lower-similarity competitive message is encountered before the company's product message.

In contrast, higher similarity between two objects enhances knowledge transfer between them (Martin and Stewart 2001). High message similarity may arise from ad execution (Kent and Allen 1994); the media used (Unnava and Sirdeshmukh 1994); message content, appeals, or positioning (Kent and Allen 1994); or the product categories being used (Keller 1987). Several researchers report high-similarity effects; for example, Burke and Srull (1988) find that high competitive message similarity caused confusion about the properties of recalled brands, thus reducing cued retrieval.

A competitor-to-A message will disrupt corporate transfer to Product A when consumers encounter a highly similar competitive message before the company's product message. Such a message positioning shares many diagnostic product associations with Product A. Therefore, processing the Product A message will activate representations of the competitor-to-A message, resulting in overlapping memory traces and making it more difficult to distinguish between the two products (Burke and Srull 1988). Consumers will try to understand how the products differ and allocate their limited cognitive resources to differentiating and categorizing them. Consequently, the competitor-to-A message becomes highly accessible and diagnostic in processing Product A (Keller 1991), providing a context for interpreting the latter. According to the accessibility–diagnosticity framework, in this situation, other accessible and diagnostic inputs, such as the previously encountered corporate message, are less likely to be used (Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988).

In the after-message sequence, the competitor-to-A message should not reduce the diagnosticity of the corporate message for judging Product A, regardless of positioning similarity. The Product A message follows the corporate message, which provides an evaluative context for judging it. Consequently, cued and accessible corporate message knowledge is relevant and diagnostic, and consumers integrate it with the product message. A unitized, elaborated representation is then stored in memory and is accessible when the consumer retrieves product knowledge to make a judgment (Meyers-Levy 1991). Thus, the subsequent competitive message does not reduce transfer.

Finally, the competitor-to-A message shares few, if any, associations with Product B and therefore is not diagnostic. The only association that Product B messages share with Product A is the use of the company's name or logo. Therefore, consumers can readily distinguish Product B from Product A, regardless of the competitor-to-A message exposure sequence and level of positioning similarity with Product A. This implies that Product A and the competitor-to-A message should be relatively inaccessible and nondiagnostic when consumers evaluate Product B. It also suggests that accessible corporate knowledge is the most diagnostic input and that the competitor-to-A message should not reduce transfer to Product B. Thus:

H_3: Corporate transfer depends on competitive message sequence and positioning similarity against a product in the portfolio. Specifically,

a. When the competitor message is encountered before a product message in the same category, it will reduce transfer when positioning similarity is high versus low.

b. When the competitor message is encountered after a product message in the same category, it will not reduce transfer regardless of positioning similarity.

H_4: A competitive message positioned against a product in the portfolio does not reduce transfer to other, unrelated products in the portfolio, regardless of message sequence and positioning similarity.

Method

Design, stimuli, and manipulations. The study was a 2 (competitive positioning similarity: high, low) × 2 (competitive message sequence: before or after the company's product message) between-subjects design with two control groups. Guided by pretests similar to those in Study 1, we designed five messages and advertisements to communicate them (see Appendix C). The company message described a hypothetical company (branded Tredegar International) in the lodging and restaurant industry by its ethical conduct, employee integrity, and charity and community efforts. We also created messages for two products in Tredegar's portfolio, a hotel (branded Dearborn) and a restaurant (branded Harvey's), and one competitive hotel product (branded Wabash). Pretests showed that none of the brand names were known or evoked any particular associations. The Dearborn and Harvey's advertisements used copy and visual imagery—pictures from magazines of the interior of a hotel room and a restaurant, respectively—to convey an upscale image. These advertisements had similar information quantity and used the headline of the company advertisement. They also contained the same retrieval cues (i.e., the company name, logo, and slogan).

The similarity manipulation varied the positioning of the competitive hotel. For the high-similarity condition, Wabash's competitive positioning was upscale, and for the low-similarity condition, it was midlevel. Message positioning was augmented with a picture of an upscale or midlevel hotel room. We pretested all images and positionings to ensure construct validity. The sequence manipulation varied when participants encountered the competitive Wabash Hotel message. The before-message sequence was Tredegar International → Wabash Hotel competitor → Dearborn Hotel → Harvey's Restaurant. The after-message sequence was Tredegar International → Dearborn Hotel → Wabash Hotel competitor → Harvey's Restaurant. Control 1 participants saw neither the corporate nor the competitive message, and Control 2 participants saw the Tredegar International message but not the competitive message.

In summary, Study 2 manipulates the relative diagnosticity of a corporate (Tredegar) and a competitive (Wabash) hotel message for making judgments about the Dearborn Hotel and Harvey's Restaurant. Specifically, the study examines how the Wabash competitive message alters transfer of the corporate message to two company products. When Dearborn and Wabash are positioned similarly and Wabash precedes Dearborn, consumers will focus on comparing the two, lessening reliance on the previously seen Tredegar corporate message and therefore reducing transfer.

Participants and procedure. Undergraduate students (n = 301) at a mid-Atlantic university participated in the experiment in exchange for extra course credit. Participants were tested in groups of approximately 25 and were randomly assigned to conditions. Participants first received a booklet that described the experiment and gave directions for answering questions (Figure 1). Instructions indicated that the study was about evaluating advertisements and products. Next, participants read that they would see some advertisements in test marketing. Then, using a projector, the experimenter showed the Tredegar International message (Control 1 participants did not see this message). Participants then recorded their Tredegar attitudes. Afterward, participants saw the Dearborn and the competitive Wabash messages and received the message sequence and positioning similarity manipulations. Control 1 and 2 participants saw only Dearborn's message. Participants then recorded their Dearborn beliefs and attitudes. Next, they answered questions about the similarity between the two hotels (seven items). Finally, all participants saw the Harvey's Restaurant message and recorded their beliefs and attitudes. They then completed potential covariate questions (i.e., service category familiarity, knowledge and usage, and corporate name awareness and knowledge). None were significant in analyses of covariance against key dependent measures. Participants also reported demographic information and tried to guess the purpose of the research (none were correct).

Measures. The key measures were Dearborn Hotel and Harvey's Restaurant beliefs and attitudes. We also used a measure of Tredegar attitude to examine a competing explanation of the results. Furthermore, we included new measures, corporate-derived Dearborn and Harvey's beliefs, which constituted an added contribution of Study 2. They sourced from the Tredegar corporate message, but we measured them in the product context (e.g., "Dearborn operates in an environmentally friendly manner"). Therefore, they directly reflect corporate transfer. Finally, we measured the manipulation check of competitive hotel similarity on seven items. The seven-point belief scales had "likely/unlikely" endpoints, which we randomly reversed. Appendix D contains measure items and reliabilities (each $\alpha > .79$).

Results

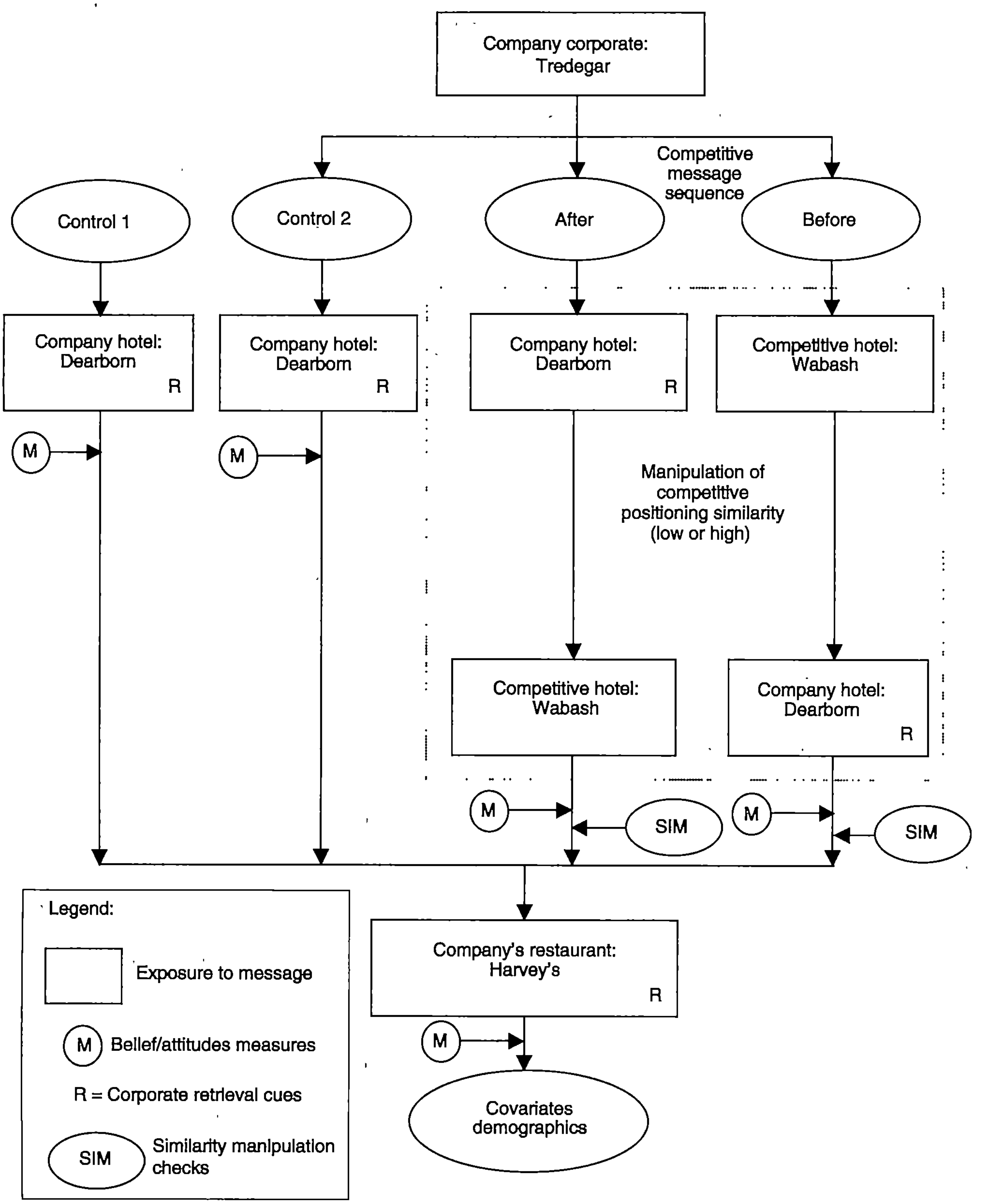
Manipulation checks. To check the similarity manipulation, we analyzed mean similarity factor scores in a 2 (competitive positioning similarity) × 2 (competitive message sequence) analysis of variance (ANOVA). Participants perceived higher similarity between the hotel and the competitive hotel in the high-similarity condition (M = 5.40) than in the low-similarity condition (M = 3.18; $t_{196} = 16.68$, $p < .0001$). No other effects were significant. To check whether the Tredegar message operated like the corporate messages used in Study 1, we compared the belief and attitude means of Dearborn Hotel and Harvey's Restaurant in the two control conditions (Table 2). All measures were higher in Control 2 (exposed to Tredegar International) than in Control 1 (not exposed, each $p < .05$). Thus, the corporate message enhanced participants' beliefs about and attitudes toward the multiple products in the company's portfolio, as in Study 1. Because this check is the sole purpose of Control 1, we do not use it anymore (i.e., subsequent references to the control condition refer only to Control 2).

Dearborn Hotel results. Table 2 contains individual cell sizes, means, and standard deviations. H_3 predicts that corporate transfer depends on competitive message sequence and positioning similarity against a product in the portfolio. In confirmation of H_3, a 2 (competitive positioning similarity) × 2 (competitive message sequence) MANOVA of Dearborn beliefs, corporate-derived beliefs, and attitude showed a two-way interaction ($F_{3, 192} = 3.34$, $p < .05$). We now explore this interaction in greater detail.

H_{3a} predicts that when the competitor message is encountered before a product message in the same category, it will reduce transfer when positioning similarity is high versus low. In confirmation of H_{3a}, Dearborn beliefs were lower in the high-similarity than in the low-similarity condition (M = 5.55 versus M = 6.01; $t_{97} = 2.49$, $p < .05$), as were corporate-derived beliefs (M = 4.10 versus M = 4.68; $t_{98} = 2.88$, $p < .01$) and attitudes (M = 5.06 versus M = 5.45; $t_{99} = 2.02$, $p < .05$).

H_{3b} predicts that when the competitor message is encountered after a product message in the same category, it will not reduce transfer, regardless of positioning similarity. Knowledge formed from the corporate message is already integrated with the product message before the competitive message is encountered, and therefore the competitive message does not influence corporate transfer. In confirmation of H_{3b}, in the high-similarity versus the low-similarity condition, Dearborn beliefs and attitudes displayed no differences (each $p > .50$).

FIGURE 1
Study 2: Experimental Procedure


Company corporate: Tredegar
Competitive message sequence
Control 1
Control 2
After
Before
Company hotel: Dearborn R
Company hotel: Dearborn R
Company hotel: Dearborn R
Competitive hotel: Wabash
M
M
Manipulation of competitive positioning similarity (low or high)
Competitive hotel: Wabash
Company hotel: Dearborn R
M
SIM
M
SIM
Company's restaurant: Harvey's R
M
Covariates demographics
Legend:
Exposure to message
M Belief/attitudes measures
R = Corporate retrieval cues
SIM Similarity manipulation checks

We expected Dearborn beliefs and attitudes to be the same across three experimental conditions: low similarity/before, low similarity/after, and high similarity/after. If this is the case, we could pool these data and compare the pooled means to the high-similarity/before means. A 3 × 1 MANOVA confirmed our expectations ($p > .30$); none of the individual 3 × 1 ANOVAs were significant (each $p > .20$; see Table 2). Furthermore, none of the three pooled

TABLE 2
Study 2: Means and Standard Deviations by Condition

	Condition					
Measure for Each Product in the Tredegar International Portfolio	**Low Similarity/ Before (n = 44)**	**High Similarity/ Before (n = 56)**	**Low Similarity/ After (n = 50)**	**High Similarity/ After (n = 50)**	**Control 2[a] (n = 50)**	**Control 1[b] (n = 51)**
Dearborn Hotel beliefs	6.01 (.82)	5.55 (.99)	6.15 (.90)	6.24 (1.04)	6.26 (.72)	5.59 (.99)
Corporate-derived Dearborn Hotel beliefs	4.68 (1.02)	4.10 (.97)	4.70 (.86)	4.50 (.88)	4.61 (.69)	4.17 (.49)
Attitude toward Dearborn Hotel	5.45 (.93)	5.06 (.98)	5.58 (1.07)	5.40 (1.34)	5.83 (.89)	4.59 (1.07)
Harvey's Restaurant beliefs	5.93 (.86)	5.73 (1.12)	5.83 (1.07)	5.99 (.85)	5.85 (1.08)	5.29 (1.19)
Corporate-derived Harvey's Restaurant beliefs	4.44 (.71)	4.62 (.76)	4.68 (.75)	4.63 (1.18)	4.41 (.71)	3.99 (.53)
Attitude toward Harvey's Restaurant	4.87 (1.55)	5.09 (1.40)	5.33 (1.10)	5.23 (1.65)	5.00 (1.27)	4.44 (1.19)

[a]Participants saw the Tredegar corporate message.
[b]Participants did not see the Tredegar corporate message.

measures differed from the respective control means (each $p > .40$), indicating no reduction in corporate transfer.

Next, we compared the pooled means with the high-similarity/before means. Dearborn beliefs were lower in the high-similarity/before condition (M = 5.55) than in the pooled conditions (M = 6.14; $t_{197} = 3.93$, $p < .0001$). This finding was replicated for Dearborn corporate-derived beliefs ($p < .001$) and attitudes ($p < .05$). Therefore, these results strongly confirm our previous results; that is, only the high-similarity/before condition reduced corporate transfer.[2]

In summary, these results confirm the conclusion that the differences predicted by the interaction hypothesis (H_3) are due to the competitive message disrupting corporate message transfer in the high-similarity/before condition. The other three conditions and the control condition showed clear evidence of corporate transfer.

Harvey's Restaurant results. H_4 predicts that a competitive message positioned against a product in the portfolio will not reduce transfer to other, unrelated products in the portfolio, regardless of message sequence and positioning similarity. In confirmation of H_4, the 2 × 2 MANOVA on Harvey's beliefs, corporate-derived beliefs, and attitudes showed a nonsignificant two-way interaction ($p > .20$) and two nonsignificant main effects (each $p > .15$). None of the relevant pairwise comparisons of Harvey's measures were significant (each $p > .15$). In particular, Harvey's beliefs and attitudes in the high-similarity/before condition did not differ from the other three experimental conditions or the controls (i.e., corporate transfer always occurred).

Discussion

Consistent with our expectations, in Study 2, we found differential competitive impacts on corporate transfer across the product portfolio; transfer depended on competitive message sequence and positioning similarity against a product in the portfolio (H_3). A reduction in transfer occurred only for Dearborn Hotel beliefs and attitudes in the high-similarity/before condition when the competing advertisement was in the same product category (H_3). However, no reduction in transfer occurred with Harvey's Restaurant, the other product in the portfolio in an unrelated category (H_4). Thus, the adverse effects of the competitive message were limited to Dearborn Hotel, the category with the competitive product, and did not spill over to other products in the portfolio, as we predicted.

General Discussion

Despite significant expenditures on corporate messages that target customers, the empirically based understanding of corporate transfer is not well developed (Brown and Dacin 1997). The two studies we report herein make important contributions to the literature by demonstrating that corporate messages have broader effects than product messages across a product portfolio. However, corporate transfer depends on the type of corporate message and a product's competitive environment.

Study 1 showed that corporate messages were more diagnostic than a product message for evaluating other products in the portfolio, whereas a product message was not diagnostic. However, a product message was more diagnostic than corporate messages for evaluating the product. In addition, we found qualitative differences in corporate transfer. Corporate ability messages were more diagnostic than CSR messages, leading to higher product beliefs and more positive product attitude. These findings are consistent with the accessibility–diagnosticity framework; that is, when consumers have multiple information sources available, they select the most diagnostic one and do not use other potentially diagnostic sources (Feldman and Lynch 1988). Therefore, Study 1 extends Brown and Dacin's (1997) findings by demonstrating that corporate transfer can occur across a product portfolio, but qualitative differences in the corporate message alter its nature and magnitude.

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[2] To buttress these findings, a reviewer suggested that we run a moderated mediation analysis to determine whether the differential effects exhibited across the experimental conditions were directly attributable to attitude toward the company. We regressed attitude toward the company, dummy (1 = the high-similarity/before condition, 2 = the other three conditions pooled), and the attitude toward the company × dummy interaction on attitude toward Dearborn Hotel. The regression was significant ($F_{3, 195} = 24.21$, $p < .0001$), as was the interaction ($F_{3, 195} = 8.84$, $p < .01$). This latter result shows that the effect of the company attitude on the hotel attitude differed between the high-similarity/before condition and the other three conditions. Specifically, in the pooled three experimental conditions, company attitude influenced hotel attitude ($F_{1, 140} = 65.37$, $p < .0001$), whereas in the high-similarity/before condition, it did not ($p > .25$).

Study 2 used a processing environment in which two messages, corporate and competitive, were potentially diagnostic for product judgments. It found that declines in transfer occurred only when the competitive message was encountered before the company's product message and was positioned similarly. In this situation, the competitive message was more diagnostic, and consequently the corporate message was not used. In the other three experimental conditions, the corporate message was more diagnostic, and the competitive message was not used. As with Study 1, these findings are consistent with the accessibility–diagnosticity framework, which predicts that when consumers have multiple information sources, they select the most diagnostic source and do not use other potentially diagnostic ones (Feldman and Lynch 1988).

Study 2 also used a qualitatively different research context from previous research. Previous research examined a single-message context (Burke and Srull 1988; Kent and Allen 1994), in which the competitive message was the only nonproduct message and thus was always diagnostic. In contrast, Study 2 examined a multiple-message context, in which the competitive message was not the only nonproduct message and was differentially diagnostic. Therefore, Study 2 broadens the view of diagnosticity and demonstrates its importance in a more realistic and complex message environment.

Finally, Study 2 found that reductions in corporate transfer were limited by product category; specifically, corporate transfer from Tredegar International to Harvey's Restaurant was unaffected by Wabash's competitive hotel message. This finding is important because it reinforces the study's methodological validity; that is, participants perceived differences across products and categorized them appropriately, some as "belonging" to the company and some as not. Furthermore, the competitive message did not spill over into unrelated product categories, even when they were similarly positioned, suggesting that participants created separate memory representations for Dearborn and Harvey's. These findings are consistent with hierarchical categorization (see Meyers-Levy and Tybout 1989), in which corporate is superordinate and product is subordinate. Transfer would be more likely across hierarchy levels (e.g., from superordinate to subordinate) but not within levels (e.g., spillover from subordinate to subordinate). In summary, the two studies provide strong empirical support for the diagnosticity of corporate messages on product portfolio judgments (Aaker and Joachimsthaler 2000) and significantly extend prior work on single-product effects (Brown and Dacin 1997; Creyer and Ross 1996).

Managerial Implications

These results have important implications for both corporate brand managers and product managers. For corporate brand managers, the critical concern is deciding whether to use CSR or CA messages to influence consumers. Corporate ability messages may be better when the objective is to enhance portfolio positioning by capitalizing on their greater diagnosticity for forming product beliefs across the portfolio versus CSR messages (as in Study 1).

This capability can be useful when products in the portfolio are similarly positioned. For example, BMW's products are all positioned on superior performance. In this context, CA messages may enhance individual product positions and thus provide communications efficiencies. Corporate ability messages may also be useful when the portfolio contains products with weak and less diagnostic positions. Here, corporate transfer may offset consumers' lack of differentiating product knowledge (see Brown and Dacin 1997). For example, in response to a loss of product differentiation and decline in sales, Levi's hopes that transfer from its CA message, "A Style for Every Story," can deliver a diagnostic belief-based positioning across its entire portfolio. However, such CA messages could make product positions less diagnostic. Consider DuPont, which markets many well-differentiated products to consumers. Its Lycra brand is positioned on fashion. Concurrently, DuPont targets its corporate message, "The Miracles of Science," to consumers. The risk is that consumers will think about all its products in the context of science, potentially undermining Lycra's positioning.

In contrast, CSR messages may work better when the objective is to maintain portfolio positioning. Corporate social responsibility messages may provide an affective "boost" without altering product beliefs. This can be useful when many products in the portfolio are dissimilarly positioned. The DuPont situation may favor CSR messages because they are less likely to undermine dissimilar and strong product positions and thus cause conflicts with product managers. Corporate social responsibility messages may also be useful when product positionings are strong and diagnostic. When the company is about to launch important new products, it typically relies on significant feature-based differentiation to succeed. For example, the Toyota Prius is strongly differentiated on outstanding gas mileage through hybrid technology. Concurrently, Toyota has run a CSR message positioned on "Made in the USA." This message is likely to be diagnostic at the product level but not as diagnostic as specific product messages. Therefore, the CSR message is less likely to jeopardize Prius's product positioning. When consumers become familiar with Prius, product attitudes formed from corporate transfer should readily shift to being formed by the product's positioning and differentiation. In this manner, CSR transfer can provide launch support until product messages kick in.

Finally, it is important for corporate brand managers to understand that corporate transfer may not occur equally across all products in the portfolio. As we found in Study 1, the same corporate message may influence Product A in one manner and Product B in another. For example, a well-known product may be less susceptible to transfer than an unknown or new product because strong, prior knowledge is more difficult to change than weak knowledge. This possibility may explain the differential product-level results in Study 1; that is, corporate messages exhibited less transfer to the credit card product than to insurance and financial planners. Recall that the common-element content (Appendix A) contained attributes for the credit card. Apparently, this content was more diagnostic for credit card belief and attitude determination than was the corporate message.

For product managers, the critical consideration is how to capitalize on corporate transfer onto their products. Product managers may have little say in the decision to use corporate messages that target consumers. In such cases, corporate messages provide a backdrop within which managers must decide how to design and deliver product messages (Biehal and Sheinin 1998). Our results suggest that they should consider three important, controllable influences on corporate transfer: the degree of product differentiation, the sequencing of product messages, and the use of corporate retrieval cues with product messaging.

Corporate transfer consistently occurred when the similarity of competitive product positioning was low (Study 2)—that is, when product differentiation was high. This suggests that product managers trying to maximize corporate transfer should maximize differentiation. In accordance with the accessibility–diagnosticity model, differentiation could serve to free up consumers' mental resources to focus on other relevant product information sources, such as corporate messages. Corporate transfer also occurred when a competitive product message was encountered after the corporate and product messages. This suggests that product managers trying to maximize corporate transfer need to know when corporate messages are scheduled so that they can place product messages as close as possible (see Sen and Bhattacharya 2001). In this way, they lessen the chance that competitive messages will precede product messages and thus reduce corporate transfer. Finally, although all our corporate messages contained corporate retrieval cues, in reality, product managers can vary their use to influence the level of corporate transfer. For example, product managers who use salient corporate retrieval cues in their product messages may get corporate transfer even when competitive messages are similar and encountered before the product messages.

Product managers' decisions may also pose potential risks for corporate brand managers when they result in product positionings that are inconsistent with a corporate message. For example, 3M's corporate message is positioned on innovation. Presumably, 3M hopes that consumers will first think "innovation" when they encounter any 3M product because of its branded-house approach (Aaker and Joachimsthaler 2000). Then, consumers will think about how that product is innovative. However, if the manager of a less innovative product, such as 3M's Highland brand, uses salient corporate retrieval cues in product messages, consumers may become confused, and the corporate positioning may become jeopardized.

This discussion implies that, in practice, corporate and product managers' decisions are closely intertwined. Consequently, companies need to develop effective organizational mechanisms for communication and cooperation. Corporate managers must understand the product portfolio, the role of various products in attaining corporate objectives, and how those products are positioned. In turn, product managers must understand consumers' corporate brand equity, particularly its content and how it influences their product judgments. This will require changing market research protocols to enable managers to tease out the contributions of corporate transfer on products. Finally, message scheduling needs to be carefully coordinated. Unfortunately, managing these concerns is typically the exception rather than the norm (Biehal and Sheinin 2001).

Limitations and Future Research Directions

The preceding discussion should be assessed with the studies' limitations in mind. In turn, these limitations suggest worthwhile areas for further research. For example, we used student samples, though careful pretesting helped maximize generalizability. Future work should consider more heterogeneous samples, including participants who are differentially loyal to the company and its products. We also used hypothetical company and product brand names. This approach is common in brand research (Brown and Dacin 1997) and reflects a concern with controlling for brand knowledge differences, but the disadvantage is weaker encoding of knowledge than with real brands. Using well-known company and product brands that vary in familiarity could lead to different levels of corporate transfer, depending on their relative accessibility and diagnosticity. Further research should attempt to understand the respective contributions of accessibility and diagnosticity to corporate transfer by taking process measures and using real company and product brands.

Another limitation was the use of a small portfolio of unfamiliar products in dissimilar categories. Although we found no evidence of product-to-product spillover, the properties of the company's product portfolio need more research attention. Recall that Study 1 found some differential transfer across the product portfolio, implying the potential presence of product heterogeneity. Many companies have well-known products that may be positioned similarly (e.g., Dell computers). Such products may constitute another diagnostic knowledge source for judging other, less familiar products in the portfolio (Dell flat-screen televisions), and thus product-to-product spillover may occur (Smith and Park 1992). Consequently, product messages may have similar influences as CA messages on other products marketed by the same firm if individual products are family branded and positioned similarly in their respective categories. However, if positioning fit in the product portfolio is lower, CA messages that can cut across the entire portfolio could be more potent than product messages.[3]

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[3] We thank a reviewer for this insight.

Examining the relative diagnosticity of consumers' corporate versus well-known product beliefs as a function of variations in portfolio positioning similarity should be another research priority.

Next, the placement of corporate messages in Study 2 limited our understanding of their effects. A reviewer suggested that corporate messages could "immunize" against competitive messages, thus protecting a differentiated position. Unfortunately, this possibility cannot be inferred from the study because participants always encountered a prior corporate message. To investigate the immunizing potential of corporate messages, further research should compare the presence or absence of prior corporate messages and the degree of product differentiation on transfer disruption that stems from competitive messages.

Finally, we examined differences between CSR and CA messages in a limited context. Although we found that CSR beliefs were relatively unimportant, in other situations, they may arise and have an influence, though one that is less enduring and weaker than CA beliefs. In addition, many other factors may moderate their relative influence on a product portfolio; research shows that the impact of a CSR message differs as consumers' support of that message changes (Sen and Bhattacharya 2001). A little-understood possibility pertains to the type of competitive message. Our study examined the adverse effect of a product-level competitive message on corporate transfer, but corporate-level competitive messages may also occur and operate similarly. If this is indeed the case, CSR and CA messages may differ in their long-term effectiveness and, thus, their susceptibility to competitive disruption. Thus, many worthwhile issues pertaining to corporate transfer need to be addressed.

Appendix A
Study 1 Stimuli

Common Elements in All Messages

- *Company name*: Atlantic Finance Company
- *Headline/slogan*: Join Our Financial Family
- *Subheadline*: Atlantic Financial is the leading supplier of financial services and planning for young people under 30.
- *Visual*: A small Visa credit card logo
- *Content*: Our Atlantic Visa card is designed with you in mind. The card offers a low 15.9% A.P.R. interest rate. Yet, you do not pay an annual fee and you receive a $5,000 credit line. In addition, you receive full collision insurance protection whenever you rent a car with the card, and total luggage loss and damage insurance whenever you purchase airline tickets with the card.
- *Execution*: Each advertisement had the foregoing elements laid out identically. The following information was also laid out identically.

CSR Message

Our mission is to be an ethical company, which conducts business with honesty and integrity. We were recently ranked in the Top 1% of U.S. companies in practicing ethical management and ethical business policies. We support our ethical standards by hiring only those people who pass strict standards of integrity. In addition, we are active in community development and support important charities. In fact, we give 5% of our total revenues to charities which benefit you, such as the U.S. Graduate School Scholarship Program and the Greater Washington Community Development Program. Our strategy has led to an annual growth rate in revenues of over 50% since 1990.

CA Message

The quality of our financial products, services, and customer service is unsurpassed in the industry. We were recently ranked #1 by *Consumer Reports* magazine for customer service quality, and in the Top 1% of U.S. Financial Services Companies in product quality by *Money* magazine. Our products and services are developed for people like you—young consumers just beginning your careers. Our service quality is maintained because we hire intelligent people your age who understand your financial questions, problems, and concerns. Our young staff is friendly, courteous, and treats you with respect. Our staff is trained to completely know all of our top-quality products and provide you with customized service.

Product Message

Our Atlantic Visa card is the ultimate in your convenience. The card is accepted at millions of retail stores, restaurants, and entertainment facilities worldwide. In addition, you can use the card at any ATM machine to withdraw cash or pay off your Visa charges. With the card, you can send or receive emergency cash at any bank or financial institution. Moreover, you get rewards for using our Atlantic Visa card, which you can redeem for cash, frequent flyer miles on any of ten major U.S. airlines, or free long distance calls. We most recently entered into Frequent Buyer agreements with the major national retailers Sports Authority, Best Buy, and Barnes & Noble Booksellers. The more you buy there with the card, the more free merchandise you will receive.

Control Message

The control contained only the common elements we described previously.

Appendix B
Study 1 Measures

Attitude Toward the Atlantic Finance Company and Each of Its Products ($\alpha s > .89$).

- "Like/dislike" (reverse scored)
- "Bad/good"
- "Positive/negative" (reverse scored)

Credit Card Product Beliefs ($\alpha = .79$)

- Convenient
- Used at ATM machines
- Build frequent flyer miles (reverse scored)
- Free long-distance calls
- Retail store discounts

Insurance Product Beliefs ($\alpha = .79$)

- Low premiums
- Immediate compensation by claims adjusters
- Protect property and possessions

Financial-Planner Product Beliefs ($\alpha = .89$)

- Certified
- Offer investment advice
- Help me plan financial future (reverse scored)
- Well trained (reverse scored)

Appendix C
Study 2 Stimuli

Common Elements in All Messages

- *Company name*: Tredegar International
- *Headline/slogan*: Feel at Home Away from Home
- *Symbol*: Globe

Corporate Message

Text. Tredegar International is a leader in the global travel industry. We also pride ourselves on our leadership in environmental responsibility and ethical business practices. Our travel services and properties are recognized for their aggressive recycling efforts by the U.S. Environmental Protection Agency. In addition, we received an Achievement Award from the Equal Opportunity Employment Commission for the diversity in our workforce. From college recruiting to upper management, our diversity is clear. We also treat our workforce well. Our employee salary and benefits package is 33% above industry norms. Our employees treat you well because we treat them well. Our 25% annual growth rate this decade to over $5 billion in global revenues is due to the hard work of our employees. When you visit one of our restaurants, resorts, hotels, or conference centers, you can be assured of a premium quality experience backed by world-wide ethical responsibility.

Visual. Two upscale-looking people relaxing in Venice.

Dearborn Hotel (a Tredegar International Product) Message

Text. Our famous Dearborn hotels have every feature and facility you need to make your stay most enjoyable and relaxing. Each room comes with a Jacuzzi, ten movie channels at no extra charge, and king size beds with premium mattresses. As if that is not enough, our hotels contain a boutique shopping arcade, a fully-equipped exercise club and pool, and a state-of-the-art game room. At Dearborn, you get everything you want from a hotel.

Visual. An upscale hotel room.

Wabash Hotel (the Competitive Product) Message

High-similarity text. Wabash Hotels are specially designed for people who enjoy life to the fullest. At all of our hotels, you'll find the staff is highly trained, ready to anticipate and meet your every need. Whether you desire a massage, need clothes laundered overnight, or require food cooked a special way, our employees will be there for you with a smile and a helping hand. At Wabash hotels, we work hard for your loyalty.

High-similarity visual. An upscale hotel room (a different room than the visual for Dearborn).

Low-similarity text. Wabash hotels are specially designed for the budget traveler. At all of our hotels, you'll find inexpensive rooms which provide the basic comforts. We know most of you don't care about fancy drapes and expensive linens when you travel. You want a comfortable room that is affordable. After all, a hotel is just somewhere you visit not somewhere you live. At Wabash hotels, you get the best value in the travel industry.

Low-similarity visual. A modest hotel room.

Harvey's Restaurant (a Tredegar International Product) Message

Text. At Harvey's, our chefs constantly search the world for new menu ideas so you can always experience something new. Feeling less adventurous? You can always rely on our regular menu favorites. Zagat's Restaurant Guide consistently ranks our restaurants among the best across the U.S. in menu diversity. At Harvey's, you get a new dining experience every time, but with the same food quality you demand and in the same atmosphere that always meets your highest expectations.

Visual. An upscale restaurant.

Appendix D
Study 2 Measures

Positioning Similarity Manipulation Check ($\alpha = .84$)

- The look of the two hotel rooms was similar.
- The two hotels would look similar on the outside.
- The two hotels would offer similar levels of customer service.
- The two hotels would have similar features. (reverse scored)
- The two hotels would have an exercise room of similar quality.
- The images of the two hotels would be similar.
- Overall, the two hotels were similar.

Attitude Toward Tredegar International, Dearborn Hotel, and Harvey's Restaurant, as Measured in Study 1 ($\alpha s > .86$)

Corporate-Derived Dearborn Hotel Beliefs ($\alpha = .82$)

- Dearborn hotels are consistent with my ethical values.
- The workforce at Dearborn hotels is diverse.
- Dearborn employees are well compensated. (reverse scored)
- Dearborn hotels operate in an environmentally friendly manner.
- Dearborn hotels are successful in terms of profits.

Dearborn Hotel Beliefs ($\alpha = .83$)

- Dearborn hotel rooms come equipped with a large variety of luxury features.

- Dearborn hotel rooms come with high-quality mattresses.
- Dearborn hotels include a fully-equipped exercise club. (reverse scored)
- Dearborn hotel rooms come with a Jacuzzi.
- Dearborn hotel rooms come with free premium movie channels.
- Dearborn hotels include a fully equipped exercise club. (reverse scored)
- Dearborn hotels include a state-of-the-art game room.

Corporate-Derived Harvey's Restaurant Beliefs ($\alpha = .80$)

- Same as corporate-derived Dearborn beliefs.

Harvey's Restaurant Beliefs ($\alpha = .87$)

- Harvey's restaurant serves a large variety of dishes.
- Harvey's offers many daily specials.
- Harvey's is ranked highly on menu diversity. (reverse scored)

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Murali K. Mantrala, Prasad A. Naik, Shrihari Sridhar, & Esther Thorson

Uphill or Downhill? Locating the Firm on a Profit Function

When deciding about changes in levels of multiple marketing investments aimed at improving profits, managers need to know whether they are on the uphill side or the downhill side of the profit function with respect to each investment variable. Spending errors made by an uphill-located firm that believes that it is a downhill-located firm can have serious consequences. This article offers an econometric "diagnostic tool" to infer a company's current location on a multivariable profit function and to determine the changes in investments that will take the company to the neighborhood of the maximum profit. The authors apply the proposed approach to daily newspaper industry data and investigate the optimality of companies' allocation behaviors with respect to three marketing efforts: investments in quality, distribution, and advertising space sales effort. A novel feature of this problem setting is that it involves a "dual-revenue" market with possibly interrelated demands for subscriptions and advertising space. The authors derive normative rules for marketing investments in four dual-revenue market types. The empirical analysis finds that daily newspapers' dual revenues are positively interrelated and that a majority of these companies are located near the optimal level of spending for quality, a surprising finding considering that previous studies have characterized marketing managers as overspenders. Indeed, when these companies are suboptimal, they are much more likely to be underspending (i.e., they are located on the uphill side of the profit function) than overspending. In addition, the research furnishes estimates of sales elasticities with respect to quality, personal selling, and distribution investments, which are sparsely available in the extant literature.

Economic theory advises managers who make marketing decisions aimed at enhancing their company's profit to operate at the "sweet spot" of a profit function, which is like a bell-shaped curve. For example, in the newspaper industry, managers can increase profit by improving news quality up to a point, beyond which further quality improvements fail to attract enough new readers to justify incremental costs. Figure 1 illustrates this reasoning and identifies the sweet spot (q*) that maximizes a profit function. On the left of this sweet spot, quality reduction reduces profit, and on the right, quality enhancement erodes profit. The real problem, however, is that companies "are being managed *as though they were on the right or downhill side* of the curve. *In fact, we believe, they are clustered on the left, or uphill side*, where degrading quality creates an imminent danger" (Meyer and Kim 2005, p. 7, emphasis added). As we describe subsequently, the lack of knowledge about the firm's location—uphill or downhill—leads managers to make serious errors in their investment decisions.

Suppose that a firm located on the uphill side of the profit function (i.e., a Type U firm) believes incorrectly that it is located on the downhill side (i.e., a Type D firm) that generates the same amount of profit (see Figure 1). Then, it will disinvest in quality and thus earn less profit (because it is really a Type U firm) rather than more profit. In the newspaper industry, this negative result could trigger what Rosenstiel and Mitchell (2004) call the "suicide spiral," in which disinvesting in newspaper quality leads to circulation decline, which leads to total revenue and profit reductions, which in turn lead to more disinvestment, more circulation decline, and further losses in revenues and profits. Similarly, a Type D firm that mistakenly believes that it is a Type U firm that makes the same profit would invest more in quality, again resulting in a profit reduction, which may induce a debilitating cycle of disinvestments in quality, falling revenues, and profits. Consequently, it is crucial for managers to be able to determine whether their company is Type U or Type D with respect to each marketing effort before they implement an appropriate course of action. A possible way for managers to determine where they are located on the profit function is to observe how both sales and profits respond to changes in spending. However, such observations do not immediately provide guidance on the change in investment level necessary to reach the sweet spot of the profit function. Furthermore, such an adaptive resolution of the problem is much more difficult and takes longer to achieve when profits are a function of spending decisions with respect to multiple marketing variables (Fraser and Hite 1988). Thus, a key purpose of this article is to offer an alternative solution, namely, an econometric "diagnostic

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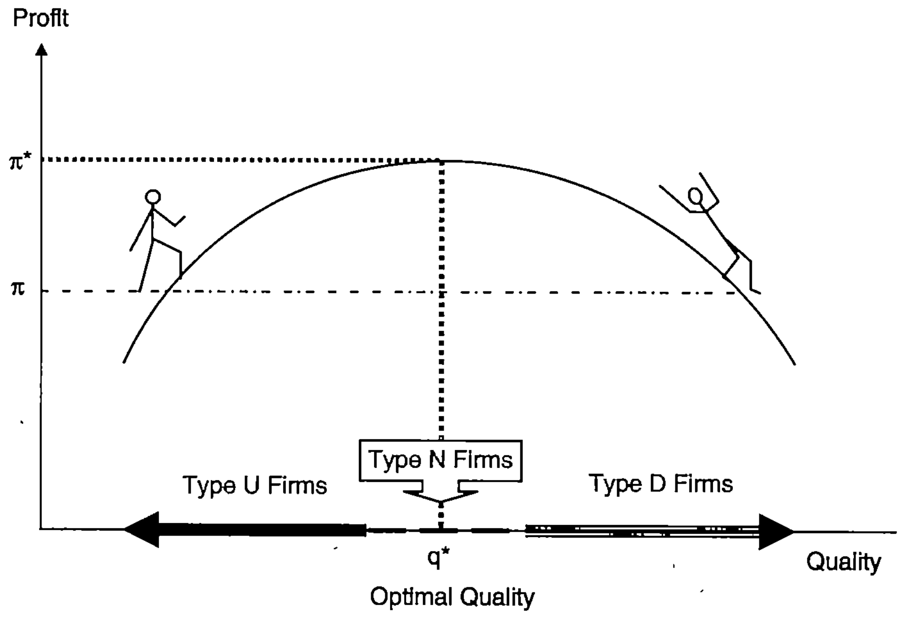
FIGURE 1
Firm Types Based on the Locations on a Profit Function



tool" to determine whether a company is Type U or Type D with respect to each variable in its marketing mix through a valid approach for statistical inference applied to data from multiple firms in an industry.

Previous research in marketing has investigated issues of measuring market impact (Rust et al. 2004)—in particular, under- or overspending on advertising (e.g., Aaker and Carman 1982; Prasad and Sen 1999). A company overspends (underspends) when the actual expenditure exceeds (is below) the optimal amount indicated by a model. However, the optimal amount itself is based on market response elasticity, which is estimated with a measure of uncertainty. How then should a manager determine whether he or she is currently at the sweet spot or whether he or she is overspending or underspending? Furthermore, how much of a deviation from the sweet spot should the manager tolerate before taking corrective action? To answer these questions, managers need a diagnostic tool to distinguish whether their firm is operating in the neighborhood of the sweet spot (i.e., Type N firm) or is significantly underspending (Type U) or overspending (Type D) (see Figure 1).

The challenge of determining whether a given company is Type N and not either Type U or Type D is to quantify an interval or a region ($\underline{x}$, $\bar{x}$) around the sweet spot x^* within which the firm is considered close to optimal, where $\underline{x} \leq x^* \leq \bar{x}$. Previous marketing studies have concentrated on determining the response elasticities and/or the optimal x^* and have not addressed this problem of estimating the triplet ($\underline{x}$, x^*, $\bar{x}$) (see, e.g., literature reviews by Gatignon [1993] and Mantrala [2002] and research on under- and overspending behaviors by Joseph and Richardson [2002], Mantrala, Sinha, and Zoltners [1992], and Naik and Raman [2003]). However, econometric theory provides a few avenues to solve this inferential problem. One approach, based on the delta method (e.g., Davidson and MacKinnon 2004, p. 202), determines the interval ($\underline{x}$, $\bar{x}$) that covers a neighborhood of x^* with 95% probability, which is obtained through an approximate normal distribution. An alternative approach that Krinsky and Robb (1986) propose avoids approximations by using Monte Carlo samples for constructing 95% coverage probability empirically. We follow the latter approach to develop a diagnostic tool for locating each firm on the profit function and, thus, for providing firm-specific diagnostic inferences with respect to each marketing effort. On the basis of actual spending decisions, we illustrate how a given company can infer whether it is Type U (below $\underline{x}$), Type N (between $\underline{x}$ and $\bar{x}$), or Type D (above $\bar{x}$) with respect to multiple marketing variables. As we discussed previously, this knowledge of a firm's type (i.e., uphill or downhill or neither) is crucial for implementing an appropriate course of action to enhance profitability.

The proposed approach yields new substantive findings. Specifically, using data from hundreds of daily newspaper firms collected by the Inland Press Association (Inland) over four years (1998–2001), we investigate the optimality of these firms' investments with respect to three marketing variables: quality, distribution, and ad space sales effort. Notably, we find that more than 70% are Type N firms; that is, a majority of these companies are located near the sweet spots for all three investments. This result is surprising because previous studies have typically characterized marketing managers as overspenders (e.g., Aaker and Carman 1982; Prasad and Sen 1999). Furthermore, we find that when firms are suboptimal in their quality and advertising sales investments, they are much more likely to underspend than overspend. This finding corroborates Meyer and Kim's (2005, p. 7) view that newspaper companies are "clustered on the uphill" of a profit function.

In addition to these two contributions (i.e., the diagnostic tool and new empirical findings), this article further augments the marketing literature in two important ways. First, we provide elasticity estimates for quality, personal selling effort, and distribution investments, which are sparsely available in the extant literature (e.g., Hanssens, Parsons, and Schultz 2001, pp. 347–49) compared with estimates of advertising or price elasticities (e.g., Assmus, Farley, and Lehmann 1984; Tellis 1988). Specifically, we find that, on average, newspaper distribution elasticity is .23, advertising sales effort elasticity is .54, and news quality elasticity is .49. This last finding should assure publishers that "good news quality is good business" (Overholser 2004).

Second, the newspaper industry offers a novel marketing context because of its "dual-revenue" market structure—that is, its sales of news to the readers and access to specialized audiences to the advertisers (Picard 1994). Furthermore, the resulting two revenue sources can be interrelated. That is, the desirability of a newspaper to advertisers and, thus, the demand for advertising space increase as circulation increases; in turn, the advertising volume a newspaper carries can influence its subscription sales (e.g., Blair and Romano 1993; Depken and Wilson 2004; Picard 1994). So far, there appears to be no research on optimal investments and allocation of marketing resources in dual-revenue markets with such demand interdependency (see Gatignon 1993; Mantrala 2002), which further motivates our normative and econometric analyses.

We organize the rest of this article as follows: In the next section, we review relevant literature pertaining to the newspaper industry's market structure and marketing efforts. Using this knowledge, we then formulate and analyze an interrelated demand model and deduce normative implications for managing dual-revenue markets. Next, we specify and estimate an econometric model, develop the diagnostic tool to infer the location of a firm on the profit function, and present the empirical results based on the Inland data. Finally, we conclude by summarizing the managerial implications.

Literature Review

Market Structure

Historically, the newspaper industry has been one of the most profitable of all industries (Picard 2004), with operating profits averaging approximately 15% and net profits averaging approximately 12% in 2001. In recent years, however, public newspaper companies are being challenged by declining circulations; for example, paid subscriptions dropped from 353 per 1000 population in 1950 to 202 per 1000 in 2000. Other challenges include printing capacity constraints, price ceilings, and competition from the Internet for classified advertising revenues. The two main characteristics of the newspaper industry are its monopoly structure and demand interrelatedness.

Monopoly. This structure is the rule rather than the exception in the U.S. daily newspaper industry. Specifically, 98% of newspapers exist as the only daily paper published in their local markets today (Blair and Romano 1993; Bucklin, Caves, and Lo 1989; Picard 1994). An explanation for the emergence of this monopoly is the "circulation–advertising death spiral": In markets in which two or more daily newspapers compete, the newspaper with the largest circulation and highest market penetration attracts a disproportionate amount of advertising—even when circulation differences are small—and secondary papers enter into a circulation death spiral of lower advertising revenues leading to disinvestments leading to lower circulation leading to lower advertising and so on, ultimately eliminating one of them from the market (Picard 1994). In the few cities in which limited competition exists, it nearly always occurs between highly differentiated newspapers, such as a broadsheet and a tabloid intended for different audiences (Picard and Brody 1997).

Demand interrelatedness. As subscription sales increase, demand for advertising space increases because the advertising cost per thousand readers reached decreases. In addition, advertisers are attracted to newspapers with large paid circulations because subscribers who pay for the newspapers are more likely to read and register their advertised messages. In turn, as we already mentioned, advertising volume in a newspaper can affect its circulation sales (Bucklin, Caves, and Lo 1989; Corden 1953; Ferguson 1983; Rosse 1967). One school of thought suggests that this impact is positive because advertising provides information on the availability of products and their prices; many consumers consider this information valuable, and those who do not can skip over it (Blair and Romano 1993). Consequently, the demand for a newspaper can increase as its advertising volume increases. Conversely, advertising may negatively affect circulation sales because it lowers the value of the newspaper to readers who want to be informed of news and not commercial messages (Abrahamson 1998). Such ad aversion may vary across cultures. For example, Sonnac (2000) provides some empirical evidence that readers' attitudes toward press advertising are country specific. Whereas U.S. readers are more typically "ad lovers," European readership seems to be "ad averse." Our research allows for and investigates both scenarios of interrelated demands.

Marketing-Mix Effects

Three major marketing-related expenditures of daily newspapers are (1) enhancing news quality, a responsibility that is managed by the editorial department, which consists of news reporters, section editors, copy editors, photographers, graphic artists, and administrative staff; (2) growing the distribution coverage, a responsibility of the circulation–distribution department, which employs telemarketers, newspaper distributors, paperboys, motor carriers, delivery truck operators, and coin-box rack technicians; and (3) generating advertiser revenues, a responsibility of the advertising department, which uses an ad space sales force with support from creative design artists and client service personnel.

News quality. The editorial department focuses on the upkeep of journalistic quality, editorial independence, and integrity. A persistent question asked in the newspaper industry is, "Is good news quality good business?" It is only recently that expenditures on news quality have begun to be viewed as a marketing investment rather than as an operating cost. Litman and Bridges (1986) put forth the concept of "financial commitment," which suggests that newsroom investment is a surrogate measure of news quality. Rosenstiel and Mitchell (2004) elucidate the concept of the suicide spiral that describes how disinvestments in quality cascade into declining subscriptions and revenues. Cho, Thorson, and Lacy (2004) empirically show that newsroom expenditures are positively correlated with quality news content, which is positively correlated with higher circulation sales. However, this stream of research stops short of providing firms with guidance on determining the optimal investment in quality.

Circulation–distribution. Distribution investments include compensation of telemarketers and delivery agents plus expenditures on delivery systems (e.g., data processing, postage, repairs, wire services). The Newspaper Association of America (NAA; 2000) has urged newspapers to view their delivery systems as strategic assets and their overall distribution investments as a means to increase sales and profit. For example, newspapers, such as the *Sacramento Bee*, increased their subscriptions and profits by developing superior delivery systems (Stein 1995).

Ad space sales. The expenditures on this effort are primarily related to sales representatives selling ad space to local retailers and companies. Smith (1998) shows that customer traffic (i.e., subscriptions and customer count), news content, and salesperson effectiveness influence firms to buy ad space in a newspaper. In a later study, Smith (2001) shows that newspapers' sales efforts tend to increase advertising revenue, which in turn can lead to more subscriptions.

Price, margins, and resource allocation. We close this review by noting the constancy of price and margins and the limited research on optimal resource allocation in the newspaper industry. Daily newspaper retail prices remain unchanged over spans of four to seven years (e.g., Bils and Klenow 2002). With regard to price of advertising space, most newspapers publish in advance their rates for retail and classified advertising of various sizes and formats, which are held fixed for at least a year. In addition, newspapers' gross margins on each circulation dollar and on each ad revenue dollar are constant because after the first copy of each day's newspaper is produced, variable costs, primarily newsprint costs, associated with the printing of subsequent copies remain constant.

Finally, the extant literature in the journalism and economics fields is descriptive with limited attention to normative analyses of marketing decisions. Two notable exceptions are the work of Corden (1953) and Bucklin, Caves, and Lo (1989), who consider maximization of a newspaper company's profit with respect to prices, product quality, and circulation-enhancing investments. However, these studies do not (1) incorporate the role of interrelated dual-revenue sources as a function of investments in quality, distribution, and advertising sales effort or (2) provide firm-specific inferences on its location on the profit function (i.e., "How far are we from the optimal?"). Therefore, we next formulate a dual-revenue market model to investigate these issues of marketing resource allocation and inference.

Model Formulation and Normative Analyses

The two revenue sources of a newspaper company are paid circulations and advertising revenue. Let S denote the number of subscribers for the year, m_1 denote the margin ($) per issue (price less the cost), and k denote the number of issues per year. Typically, k equals the number of days in the year; so k = 730 when some newspapers produce both morning and evening editions. Let R denote revenues from all advertiser sources (e.g., retail and classified advertising) and m_2 denote the margin ($) per advertising dollar generated. On the basis of the literature review, subscription sales S and advertising revenue R depend on investments in news quality, distribution coverage, and ad space sales effort. More specifically, in line with the work of Cho, Thorson, and Lacy (2004) and Stein (1995), investments in news quality and circulation–distribution directly influence subscriptions, and the investment in ad space sales effort directly influences advertising revenue (Smith 2001). The circulation–distribution effort does not directly affect advertising revenue, because it is focused on ensuring newspaper delivery to the subscribers; it is not aimed at advertisers. Similarly, the ad space sales effort does *not* directly affect subscriptions, because it is focused on retailers and companies, not on readers. However, the resulting ad revenue can influence the level of subscriptions, which in turn directly affects ad revenue (e.g., Blair and Romano 1993; Bucklin, Caves, and Lo 1989; Corden 1953; Ferguson 1983; Rosse 1967). Conceptually, therefore, a simultaneous rather than recursive model of a newspaper's dual-revenue relationship to the marketing mix is warranted. Thus, denoting (q, d, a) as dollars invested in quality, distribution, and advertising sales, respectively, we express the dual-revenue sources as follows:

$$S = f_1(q, d, R), \text{ and} \tag{1}$$

$$R = f_2(a, S), \tag{2}$$

where $f_1(\cdot)$ and $f_2(\cdot)$ are general diminishing-returns response functions as is commonly assumed in marketing-mix analyses—specifically, $\partial f_i/\partial x > 0$, $\partial^2 f_i/\partial x^2 \leq 0$, i = 1, 2, and x = q, d, a, R, S as necessary, with the system allowing for interrelated demands; that is, advertising revenue R directly affects subscriptions in Equation 1, and subscriptions directly influence advertising revenue in Equation 2.

Summing the two revenues and deducting the expenditures on quality, distribution, and ad space sales, we obtain the firm's profit as follows:

$$\pi(q, d, a) = m_1 \times k \times S + m_2 \times R - q - d - a. \tag{3}$$

To determine the optimal investment levels in quality (q^*), distribution (d^*), and advertising sales (a^*), we differentiate Equation 3 with respect to (q, d, a) and solve the resulting three first-order conditions simultaneously. We relegate these details to Appendix A and subsequently describe the analytical results presented in Table 1, focusing our appro-

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TABLE 1
Investment Decision Rules Across the Four Market Types

Market Types, j	**1**	**2**	**3**	**4**
Characteristics	Unrelated markets	Partially related markets	Interrelated markets with opposing feedback	Interrelated markets with positive feedback
Conditions	$\partial f_1/\partial R = 0; \partial f_2/\partial S = 0$	$\partial f_1/\partial R = 0; \partial f_2/\partial S > 0$	$\partial f_1/\partial R < 0; \partial f_2/\partial S > 0$	$\partial f_1/\partial R > 0; \partial f_2/\partial S > 0$
Cross-market dependency	$\delta = 1$	$\delta = 1$	$\delta > 1$	$\delta < 1$
Quality decisions	q_1^*	$q_2^* > q_1^*$	$q_3^* < q_2^*$ $q_3^* > q_1^*$ if and only if $m_2/(km_1) > \lvert\partial f_1/\partial R\rvert$	$q_4^* > q_2^* > q_1^*$
Distribution decisions	d_1^*	$d_2^* > d_1^*$	$d_3^* < d_2^*$ $d_3^* > d_1^*$ if and only if $m_2/(km_1) > \lvert\partial f_1/\partial R\rvert$	$d_4^* > d_2^* > d_1^*$
Advertising decisions	a_1^*	$a_2^* = a_1^*$	$a_3^* < a_2^*$	$a_4^* > a_2^* = a_1^*$

priate decision rules for the various special cases or types of dual-revenue markets.

Specifically, we identify four types of markets based on the cross-market dependency coefficient

$$\delta = 1 - \frac{\partial f_1}{\partial R}\frac{\partial f_2}{\partial S},$$

which arises in Equation A4 (see Appendix A). The presence of this dependency coefficient makes the optimality conditions for dual-revenue markets different from those in the standard analysis (Dorfman and Steiner 1954; see also Hanssens, Parsons, and Schultz 2001, pp. 358–61). The four types of markets are as follows.

Market Type 1: unrelated markets. In this special case, the two revenue sources are not related; that is, $\partial f_1/\partial R = 0$, and $\partial f_2/\partial S = 0$, so the dependency coefficient equals unity (i.e., $\delta = 1$). Although this market is valid for other industries and is analyzed by Dorfman and Steiner (1954), it is unlikely to prevail in the daily newspaper industry.

Market Type 2: partially related markets. Here, an increase in the number of subscriptions increases advertising revenues, but not vice versa; that is, $\partial f_2/\partial S > 0$, and $\partial f_1/\partial R = 0$. Corden (1953) and Bucklin, Caves, and Lo (1989) analyze this market setting, and it differs from the current study because we identify and analyze interrelated demand markets, as we describe subsequently.

Market Type 3: interrelated markets with opposing feedback effects. This market arises when increased subscriptions beget larger advertising revenues, but the resulting enhanced advertising volume reduces the number of subscribers, thus implying negative feedback from advertising revenues to subscriptions; that is, $\partial f_2/\partial S > 0$, and $\partial f_1/\partial R < 0$. Abrahamson (1998) and Sonnac (2000) suggest such a market on the basis of the argument that increasing volumes of advertising cause reader irritation and erode the utility a subscriber gets from the newspaper. We empirically test the implied hypothesis, H_0: $\delta > 1$.

Market Type 4: interrelated markets with positive feedback effects. Rosse (1967), Ferguson (1983), and Blair and Romano (1993) provide support for the presence of such markets, in which both feedback effects are positive; that is, $\partial f_1/\partial R > 0$, and $\partial f_2/\partial S > 0$. Empirically, to distinguish this possibility from Type 3 markets, we need to test whether H_0: $\delta < 1$ holds.

The various market types induce different investment behaviors from managers. Table 1 summarizes the optimal investments in quality q_j^*, distribution d_j^*, and advertising sales a_j^*, where j indicates the market type (j = 1, 2, 3, or 4). For markets of Type 1, we recover the usual optimality conditions stated in Dorfman and Steiner's (1954) theorem. For markets of Type 2, because of positive feedback from subscriptions to ad revenues, the optimal investments in quality and distribution are larger than those for unrelated markets (i.e., $q_2^* > q_1^*$ and $d_2^* > d_1^*$), whereas the optimal advertising sales expenditure remains the same ($a_2^* = a_1^*$). Next, for markets of Type 3, managers should reduce their investments in news quality, distribution, and advertising sales compared with those made for partially related markets (i.e., $q_3^* < q_2^*$, $d_3^* < d_2^*$, and $a_3^* < a_2^*$). Intuitively, increasing the investments is counterproductive because advertising revenues hurt subscriptions in this market. When we compare Market Types 3 and 1, we find again that managers in Market Type 3 should invest less in news quality and distribution than the corresponding levels for Market Type 1 (i.e., $q_3^* < q_1^*$ and $d_3^* < d_1^*$), except when the margin ratio exceeds the feedback effect (i.e., $m_2/km_1 > \lvert\partial f_1/\partial R\rvert$). In other words, investments in quality and distribution that are greater than the optimal levels for Market Type 1 are justified in Market Type 3 only if profit contributed by the increased advertising revenue exceeds the lost contribution due to lower subscriptions. In contrast, when we compare Market Types 4 and 1, we observe that managers in Market Type 4 should increase the investments in quality, distribution, and advertising sales beyond the corresponding levels for Market Type 1 because positive feedback reinforces both subscription and advertising revenues.

In summary, the normative analysis reveals four market types and appropriate decisions for each one. Furthermore, previous research pertains only to Market Types 1 and 2 (see Bucklin, Caves, and Lo 1989; Corden 1953; Dorfman and Steiner 1954). Consequently, we identified new markets (i.e., Market Types 3 and 4); derived the optimal investments in quality, distribution, and advertising; and gained insights into different decision rules applicable across these markets. Notably, investment decisions in Market Type 3 tend to be opposite of those for Market Type 4 (for details, see Table 1). Thus, managers need to know the type of market they operate in, an empirical issue that we examine in the next section.

Empirical Analyses and Diagnostic Tool

In this section, we present empirical analyses of Inland daily newspaper data that enable us to develop and demonstrate two diagnostic procedures: (1) an approach for managers to determine the type of market (Type 1, 2, 3, or 4) in which they operate and (2) a tool to assess whether their firm is overspending or underspending and to offer guidance for driving it to the neighborhood of the maximum profit. Determination of market type depends on the estimation of the cross-market dependency coefficient. To this end, we first describe the data sets, model specification, and estimation approach, and then we present the empirical results for cross-market dependency and elasticity estimates for advertising sales, distribution, and quality. Subsequently, we propose the diagnostic tool, which is based on a five-step algorithm, to locate a specific company on the multivariable profit function and thus infer whether it is a Type N firm (near-optimal spending), a Type U firm (underspending), or a Type D firm (overspending) with respect to each of the marketing investments.

Inland Data

Inland Daily Press Association constructs annual data sets that "tell us more about the economic innards of American dailies than any other source" (Blankenburg 1989, p. 98). Inland data sets contain information from yearly samples of hundreds of individual newspapers with circulations that do not exceed 85,000, which constitutes a representative cross-section of the total 1400 U.S. daily newspapers (Picard 1989, p. 110). Our research uses Inland data collected in 1998, 1999, 2000, and 2001. Because newspaper companies desire confidentiality, Inland data sets do not reveal information about their identities and locations. Each year's data set contains information about participating newspapers' subscriptions (S), advertising revenues (R), and margins on sales and ad revenues (m_1, m_2). In addition, we have data on the firms' annual investments in news quality, circulation–distribution, and advertising sales activities. Specifically, news quality investment (q) equals the sum of news editorial expenses, newsroom salaries, and miscellaneous expenses; distribution investment (d) equals the sum of distribution expenses, distribution department salaries, and miscellaneous expenses; and advertising sales investment (a) equals the sum of expenses to reach potential advertisers, ad department salaries, and miscellaneous expenses.

Response Model Specification

Consistent with the theoretical model expressed in Equations 1 and 2, we specify the two-equation simultaneous system of a newspaper company's dual demands as follows:

$$S_i = \alpha_0 + \alpha_1 R_i + \alpha_2 \mathrm{Ln}(q_i) + \alpha_3 \mathrm{Ln}(d_i) + \varepsilon_i \text{, and} \tag{4}$$

$$R_i = \beta_0 + \beta_1 S_i + \beta_2 \mathrm{Ln}(a_i) + \nu_i, \tag{5}$$

where S_i denotes the annual number of subscribers (in thousands); R_i represents ad revenue (in hundreds of thousands of dollars); $\mathrm{Ln}(\cdot)$ is the natural logarithm; and (q_i, d_i, a_i) are dollars invested in quality, distribution, and advertising sales, respectively, by the newspaper companies $i = 1, ..., N$.

In Equations 4 and 5, we use the semilog specification of the effects of changes in news quality and distribution investments on subscriptions and the effect of changes in ad sales effort on advertising revenues because of its consistency with the theoretical assumption of diminishing returns, parsimony, and popularity in previous advertising research (see, e.g., Carroll, Green, and Desarbo 1979; Lambin 1969; for a discussion of the semilog response model's advantages, see Doyle and Saunders 1990). Response elasticities based on the semilog model are easily interpreted and yield closed-form analytical expressions for optimal levels of the marketing investments.

We expect that the quality investment response coefficient α_2, the circulation–distribution investment coefficient α_3, and the advertising sales investment coefficient β_2 will be positive. We also expect that the impact of subscriptions on ad revenues β_1 will be positive, but the impact of ad revenues on subscriptions α_1 may be zero, positive, or possibly negative. To sign the intercept term β_0 in Equation 5, we note that advertisers will not advertise in a newspaper unless it has some minimum positive subscriptions. Therefore, if the newspaper's advertising effort is negligible (e.g., close to \$1), subscription sales must be greater than $(-\beta_0/\beta_1) > 0$ for advertising revenues to be positive. Consequently, given $\beta_1 > 0$, the intercept $\beta_0 < 0$.

Turning to Equation 4, we note that a minimum investment in news quality (editorial or newsroom employees) is necessary to avoid closing the newspaper. If we assume this minimum investment in quality, which will provide for some minimum subscription sales, the intercept α_0 in Equation 4 implicitly captures the incremental impact of the annual carryover effect of previous distribution investments.

Finally, we assume that the random errors, ε_i and ν_i, are normally distributed with zero means and constant variances (σ_ε^2, σ_ν^2) and are possibly correlated ($\rho_{\varepsilon\nu}$) because common economic conditions affect both subscriptions and ad revenues. In summary, the specifications of Equations 4 and 5 satisfy all the theoretical assumptions; that is, $\partial E[S_i]/\partial z > 0$, $\partial^2 E[S_i]/\partial z^2 \leq 0$, $\partial E[R_i]/\partial z > 0$, and $\partial^2 E[R_i]/\partial z^2 \leq 0$ for every firm i and every argument $z = q_i, d_i, a_i, R_i$, and S_i.

Accounting for Heterogeneity in Model Parameters Across Newspapers

Equations 4 and 5 assume that the model parameters are identical across newspapers, which may not be a realistic assumption when we consider heterogeneity due to location, population, economic development, diversity, and retail business concentrations across our annual, cross-sectional samples of newspapers. For example, subscriptions and ad revenues of newspapers located in smaller cities can be systematically more or less responsive to quality investment efforts than those of newspapers located in larger city markets. To incorporate heterogeneity, we partition the annual Inland samples into homogeneous subgroups or segments using latent-class clustering (LCC); alternatively, a random coefficients model (Swamy 1970) could be estimated (e.g., Rao, Agarwal, and Dalhoff 2004).

Although the Inland data sets do not provide any direct information about the identities and geographic locations/markets of newspapers, they contain data on several related variables: total salaries of all employees, number of newsroom employees, number of circulation–distribution employees, and number of advertising department employees. As we explain subsequently, these variables not only reflect firms' sizes but also serve as indicators of the categorical latent variable for classifying newspapers into groups with similar geographic characteristics.

Total salaries (TOTSAL). In the United States, significant variation exists in the wages paid for particular jobs in different geographic locations and regions (see, e.g., Mercer Human Resources Consulting's "2005 Geographic Salary Differentials" study at www.imercer.com). Such geographic variation in salaries reflects heterogeneity in the cost of labor (i.e., differences between localities in terms of cash compensation for the same work) and the cost of living (i.e., difference between localities in terms of cost of housing, groceries, transportation, and entertainment). Furthermore, market pay for lower-paid and lower-level employees varies more with geography than it does for higher-paid and more senior employees because, in general, employers recruit for lower-paying jobs from the local population. The Readership Institute at Northwestern University reports that newspapers recruit more than 84% of their employees from outside the newspaper, and the bulk of these external hires is rank-and-file or lower-paying jobs staffed from within the newspaper's community or market (see "1999 Workforce Characteristics Survey" at www.readership.org). This observation and the fact that most daily newspapers have only one primary office location and few or no secondary locations suggest that variations in total salaries across newspapers reflect differences in the cost of labor and cost of living in their headquarter towns and environs.

Number of newsroom employees (NEMP). According to the Readership Institute's "1999 Workforce Characteristics Survey," on average, 35% of the employees of a newspaper work in the newsroom (i.e., news editorial department). Although an industry guideline calls for one newsroom employee slot per 1000 circulation, larger newsroom staffs exist among papers that produce more zoned editions, which offer more specialized coverage for a host of special interest groups, including ethnic groups (e.g., Hispanics) and affluent immigrant groups (Rosentiel and Mitchell 2004). Thus, newspapers in locations with more diversity and/or higher education and income levels are likely to have more newsroom employees.

Number of circulation–distribution employees (DEMP). Circulation department employees account for another 35% of a newspaper's total employees (see "1999 Workforce Characteristics Survey" at www.readership.org). These employees ensure delivery of the newspaper to all its subscribers and other outlets in the newspaper's market. Consequently, we expect that newspapers with greater numbers of circulation department employees are located in more urban areas with larger populations.

Number of advertising department employees (AEMP). On average, approximately 25% of a newspaper's staff work in the advertising department to generate advertising revenues. A large proportion of these employees constitute the ad space sales force. We expect that newspapers with higher numbers of advertising department employees and, thus, larger advertising sales force sizes are located in areas with greater numbers of business accounts.

Using these four indicators, we incorporate heterogeneity into the model parameters due to observed and unobserved characteristics of newspaper firms and their geographic markets through a three-step latent-class segmentation–estimation approach. In the first step, we employ LCC analysis (e.g., Vermunt and Magidson 2003) using the four indicators to identify clusters of newspapers with similar characteristics. Because LCC formulates a finite mixture of multivariate normal distributions, it provides probabilistic classification of newspapers into clusters, does not require rescaling of observed variables, and yields managerially meaningful segments (e.g., Wedel and Kamakura 2000, pp. 78, 329). We used the software Latent Gold Version 3.0.6 for this purpose. The LCC model includes a K-category latent variable, which we measured with the four indicators, in which each category represents a cluster. Because the appropriate number and composition of latent segments are not known a priori, we investigate different LCC scenarios, such as one-segment, two-segment, and three-segment solutions. In the second step, we estimate the simultaneous equations (4 and 5) by segment under different clustering scenarios. In each of these model estimations, we allow for the possibility of correlated errors and employ the three-stage least squares (3SLS) estimation approach that uses complete information on both the structural equations. (We applied the Lagrange-multiplier test [e.g., Greene 2000, p. 492] in each estimation scenario to establish that 3SLS estimation was more efficient than the 2SLS estimation procedure, which ignores the correlation between errors.) In the third step, we select the best segmentation–estimation model by applying the mixture regression criterion (MRC), which Naik, Shi, and Tsai (2007) developed. The MRC extends the classical Akaike information criterion to finite mixture regression models by theoretically deriving a clustering penalty term to prevent overclustering (i.e., inclusion of insignificant segments). Thus, MRC is given by

$$(6)\qquad \text{MRC} = \sum_{l=1}^{L} \{\hat{n}_l \text{Ln}(\hat{\sigma}_l^2) + \frac{\hat{n}_l(\hat{n}_l + p_l)}{\hat{n}_l - p_l - 2} - 2\hat{n}_l \text{Ln}(\hat{\phi}_l)\},$$

where L is the total number of segments; $\hat{n}_l$ denotes the number of firms in Cluster l; p_l denotes the number of estimated parameters, $\hat{\sigma}_l^2 = \hat{\sigma}_\varepsilon^2 + \hat{\sigma}_v^2$, from the simultaneous equation estimation of each cluster; and $\hat{\phi}_l$ (≤ 1) denotes the proportion of sample classified in Cluster l.

By applying the three-step segmentation–estimation approach to the Inland data, we find that the MRC achieves its minimum value with the two-segment model in each year (see Table 2). In other words, the two-segment model balances both the fidelity (i.e., superior fit) and the parsimony (i.e., fewer parameters) better than the one- or three-segment models.[1] In the remainder of this section, we examine these results in greater depth.

Description of Two Newspaper Company Segments

In each of the four years, the Wald statistics associated with the parameters of each of the four indicators in the two-segment clustering solution were significant at the 95% level of confidence, establishing that they were useful in exposing latent differences among the segments of newspaper firms. Furthermore, newspapers assigned to Segment 1 have high probabilities of having smaller observed values on each of the four indicator variables. Table 3 displays the sizes and indicator profiles of the derived segments. We observe that in each year, Segment 2 consists of newspapers whose average total salaries are approximately 4 times larger than the corresponding mean total salaries of newspapers in Segment 1. In addition, the mean numbers of newsroom, circulation department, and advertising sales employees of Segment 2 newspapers in each year are more than 2.5 times larger than those of Segment 1 newspapers. Hereinafter, we refer to Segment 2 (Segment 1) as the "large-firm" ("small-firm") segment. If we average across the years, 57% of all firms fall in the small-firm segment.

Next, Table 4 reports the means and standard deviations of the three input investment variables, subscription sales, ad revenues, and margins for the two segments in each year. We observe that the large-firm segment's mean investments in quality, distribution, and advertising sales effort are 3.5 to 5 times greater than the corresponding small-firm segment's mean investments. Furthermore, in each year, the large-firm segment's mean subscription sales are approximately 3 times greater and advertising revenues are more than 4 times greater than those of the corresponding small-firm segment.

Two-Segment Simultaneous Equation Model Estimation Results

Estimates of model parameters. Table 5 reports the segment-by-segment dual-revenue response model parameter estimates across the 1998–2001 period. First, on the basis of R-square values that range from .77 to .86, the proposed simultaneous equation model for subscription and ad revenues fits each segment's data in each year satisfactorily. Second, across the four years, the estimated slope coefficients of all the variables have the correct signs. In addition, across all segments and years, the estimated intercepts (β_0) possess the expected negative sign and remain significant at the 90% or greater confidence level.

Third, 10 of the 12 investment coefficient estimates in the small-firm segment across the four years are statistically significant at the 95% confidence level, and 7 of the 12 estimated investment coefficients in the large-firm segment are significant at the 90% confidence level. Focusing on the small-firm segment model estimation results, we observe that the estimated coefficients for investments in quality (α_2) and advertising sales effort (β_2) are statistically significant at the 95% confidence level in all four years, whereas the distribution coefficient estimate (α_3) is not significant in 1998 and 1999 but is significant at the 95% confidence level in 2000 and 2001. The corresponding significance results in the large-firm segment are mixed. In this segment, none of the investment coefficient estimates are significant in 1998, the quality investment is significant at the 95% confidence level only in 1999, and the distribution and advertising sales investment coefficients are statistically significant at the 95% confidence level in 1999 and at the 90% confidence level in 2000 and 2001. Overall, we find that investments in newspaper quality have consistently significant, positive effects in the small-firm segment, whereas advertising sales

TABLE 2
Model Selection Based on MRC

Year	One Segment	Two Segments	Three Segments
1998	3272.60	3212.93	3266.47
1999	4495.96	4392.1	4810.24
2000	3791.56	3761.21	3825.59
2001	3692.35	3656.72	3657.17

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[1] We also estimated an alternative recursive model formulation that a reviewer suggested—in which subscriptions directly affect advertising revenues but advertising revenues do not directly affect subscriptions—on the four annual Inland data sets and found that the minimum MRC value in each case was again achieved with the two-segment solution but that it was larger than the corresponding MRC value we obtained with the proposed simultaneous equation model. Given its superior fit to the data and its consistency with observations in the newspaper marketing and research literature, we focus on the proposed model-based results in the rest of this article.

TABLE 3
Descriptive Statistics of Cluster Indicators

	Segment 1 (Small Firm)		Segment 2 (Large Firm)	
	M	SD	M	SD
		1998		
Segment Size (%)	57		43	
TOTSAL ($)	982,147	531,883	3,971,579	1,983,417
NEMP	19	1.04	53	2.2
AEMP	13	.65	38	1.8
DEMP	9	.63	39	2.5
		1999		
Segment Size (%)	52		48	
TOTSAL	941,181	490,293	4,061,622	1,995,758
NEMP	17	.66	53	1.69
AEMP	13	.49	41	1.91
DEMP	8	.43	37	1.71
		2000		
Segment Size (%)	55		45	
TOTSAL	1,119,222	570,862	4,552,234	2,135,199
NEMP	19	.81	57	2.10
AEMP	14	.66	40	1.38
DEMP	10	.54	39	2.10
		2001		
Segment Size (%)	69		31	
TOTSAL	1,410,944	779,374	5,492,816	2,326,251
NEMP	22	.9	64	3.06
AEMP	17	.7	45	1.79
DEMP	12	.65	46	2.7

investments tend to have significant, positive effects in both small-firm and large-firm segments.

Fourth, we note that in both segments and in all four years, subscription sales have a positive, statistically significant impact on advertising revenues, and similarly, advertising revenues have a positive, significant impact on subscription sales, except for the small-firm segment in 1998 when the advertising revenues impact on subscriptions was not significant. Next, on the basis of these results, we investigate whether the newspaper market type is one of interrelated demands (Types 3 or 4), partially related demands (Type 2), or unrelated demands (Type 1) in the four years under study.

Determining the market type. To this end, we test a set of hypotheses hierarchically as follows: We test whether $\delta > 1$ with a one-tailed t-test; if it holds, the market is Type 3. If not, we test whether $\delta < 1$ with a one-tailed t-test; if it holds, the market is Type 4. Otherwise $\delta = 1$, and so we test whether $\beta_1 = 0$ with a two-tailed t-test. If it holds, the market is Type 1; if not, it is Type 2. To conduct these tests, we need to evaluate the mean $E[\delta]$ and the variance $Var[\delta]$, which we derive in Appendix B. For example, for the 1998 estimates of (α_1, β_1) in the large-firm segment given in Table 5, we find that the estimated mean equals .482 and the variance is .057, which indicates that $\delta < 1$; thus, this market is Type 4 (i.e., interrelated markets with positive feedback). Similar results emerge for the large-firm segment in all the remaining years and in the small-firm segment with the sole exception of the result in 1998, for which the t-value suggests that $\delta = 1$ (see Table 6). Furthermore, in this case, Table 5 indicates that we must reject $\beta_1 = 0$; thus, this market is Type 2 (i.e., partially related). Overall, our empirical findings corroborate the markets that Corden (1953) and Bucklin, Caves, and Lo (1989) describe and furnish reasonable support for the idea that U.S. daily newspapers operate in markets of Type 4, which are characterized by interrelated demands for subscriptions and advertising space with positive feedback effects. This conclusion is also consistent with Sonnac's (2000) observation that newspaper readers in the United States tend to be ad lovers.

Newspaper Quality, Distribution, and Selling Effort Elasticities

Table 7 reports the overall and segment-level elasticities of both subscription sales and advertising revenues with respect to the three marketing activities in each year. First, the estimates of quality, distribution, and personal selling elasticities in the daily newspaper industry are consistent with prior, albeit sparsely available, estimates in the marketing literature (e.g., Hanssens, Parsons, and Schultz 2001). Specifically, averaging across the two segments and four years, we obtain the mean elasticities. The elasticity of subscription sales and advertising revenues with respect to news quality investments are .49 and .55, respectively, which are consistent with the overall quality elasticity estimates of .521 and .611 that Lambin (1976) and

TABLE 4
Descriptive Statistics by Segments

	Segment 1 (Small Firm)							
	1998 (N = 140)		1999 (N = 170)		2000 (N = 158)		2001 (N = 193)	
Variables	M	SD	M	SD	M	SD	M	SD
Quality investments (in thousands of dollars), q	1058.7	615.1	999.6	548.5	1159.4	612.2	1467.6	842.6
Distribution investments (in thousands of dollars), d	653.1	416.1	640.0	395.6	780.3	461.1	1022.7	691.4
Ad sales investments (in thousands of dollars), a	844.6	451.9	807.1	431.3	980.7	552.5	1231.3	740.4
Subscriptions sales (in thousands of dollars), S	13.9	7.5	12.7	6.4	13.7	6.5	16.3	8.5
Advertising revenue (in hundreds of thousands of dollars), R	36.1	25.6	33.5	22.1	39.5	25.02	49.9	33.8
Subscription margin, m_1	.17	.06	.17	.06	.16	.05	.17	.06
Ad revenue margin, m_2	.71	.14	.75	.14	.76	.15	.77	.17

	Segment 2 (Large Firm)							
	1998 (N = 107)		1999 (N = 157)		2000 (N = 128)		2001 (N = 85)	
Variables	M	SD	M	SD	M	SD	M	SD
Quality investments (in thousands of dollars), q	4054.5	2065.5	4094.9	201.9	4637.7	2222.7	5519.1	2483.5
Distribution investments (in thousands of dollars), d	3038.9	1819.3	3089.5	173.4	3428.8	1952.7	4284.1	2110.1
Ad sales investments (in thousands of dollars), a	3025.5	1444.4	3236.6	158.3	3487.8	1511.1	4010.2	1712.1
Subscriptions sales (in thousands of dollars), S	39.7	16.7	39.35	16.4	41.2	16.2	47.07	16.7
Advertising revenue (in hundreds of thousands of dollars), R	144.6	80.2	155.8	88.5	169.01	84.3	190.7	85.7
Subscription margin, m_1	.21	.09	.21	.08	.19	.08	.19	.09
Ad revenue margin, m_2	.75	.11	.79	.09	.78	.11	.79	.12

TABLE 5
Parameter Estimates (t-Values) for the Dual-Revenue Model

	1998		1999		2000		2001	
Parameters	**Segment 1 (Small Firm)**	**Segment 2 (Large Firm)**	**Segment 1 (Small Firm)**	**Segment 2 (Large Firm)**	**Segment 1 (Small Firm)**	**Segment 2 (Large Firm)**	**Segment 1 (Small Firm)**	**Segment 2 (Large Firm)**
Intercept, α_0	–86.9	–142.8	–57.51	–273.1	–61.06	–176.28	–83.58	–183.4
	(–2.49)	(–1.60)	(–2.32)	(–3.33)	(–4.06)	(–1.65)	(–3.67)	(–1.74)
Ad revenue coefficient, α_1	.07	.13	.12	.06	.11	.09	.09	.11
	(.94)	(2.96)	(1.93)	(1.69)	(3.15)	(2.06)	(2.32)	(2.81)
Quality coefficient, α_2	5.79	5.66	4.13	12.1	3.8	8.5	3.96	8.94
	(2.54)	(1.57)	(2.22)	(3.06)	(3.46)	(1.61)	(2.63)	(1.57)
Distribution coefficient, α_3	1.41	5.25	.73	8.02	1.32	4.77	2.92	4.63
	(1.38)	(1.59)	(1.39)	(2.92)	(2.31)	(1.69)	(3.60)	(1.91)
Intercept, β_0	–147.3	–467.2	–103.1	–554.3	–165.04	–473.33	–232.59	–660.11
	(–3.49)	(–1.75)	(–2.92)	(–3.60)	(–4.52)	(–2.25)	(–4.68)	(–2.1)
Subscription coefficient, β_1	2.38	3.83	2.67	4.16	2.4	4.55	2.49	4.08
	(7.47)	(6.23)	(8.30)	(10.60)	(6.91)	(9.55)	(7.05)	(6.61)
Ad sales effort coefficient, β_2	11.15	30.99	7.6	36.7	12.5	30.34	17.4	43.53
	(3.25)	(1.59)	(2.63)	(3.28)	(4.20)	(1.99)	(4.39)	(1.94)
Error variance σ_ε^2	1575.8	5513.36	1315.4	7909.4	1038.8	6349.6	2433.3	3993.3
Error variance σ_v^2	10,743.5	143,720.8	13,511.5	233,236.3	15,302.3	131,639.2	34,399.1	101,010.6
Subscription model fit, R^2	.79	.80	.80	.81	.83	.81	.81	.82
Ad revenue model fit, R^2	.86	.77	.81	.79	.81	.84	.82	.83

TABLE 6
Determination of Market Type

Parameters	1998 S1	1998 S2	1999 S1	1999 S2	2000 S1	2000 S2	2001 S1	2001 S2
α_1	.07	.13	.12	.06	.11	.09	.09	.11
β_1	2.38	3.83	2.67	4.16	2.4	4.55	2.49	4.08
E[δ]	.832	.482	.670	.744	.733	.571	.771	.541
Var[δ]	.041	.057	.037	.021	.009	.061	.01	.031
t-value	–.83	–2.17	–1.72	–1.76	–2.82	–1.75	–2.34	–2.62
Market type	2	4	4	4	4	4	4	4

Notes: S1 and S2 denote the small-firm and large-firm segments, respectively.

Ramaswamy and colleagues (1993), respectively, report. Next, we obtain mean subscription–distribution and advertising revenue elasticities of .23 and .26, respectively, which fall in the range of previously reported distribution elasticities for cigarettes (.18), automobiles (.49), and VCRs (.49) (see Andrews and Franke 1996). Finally, the mean elasticity of .54 for the ad revenue response with respect to ad space sales effort is consistent with previous estimates of .5 (ranges from .26 to .98) that various studies on youth enlistment in the military report (e.g., Hanssens and Levien 1983; see also Ramaswamy and colleagues' [1993] profit impact of market strategy data-based study). However, the mean elasticity of subscription sales to ad space sales effort is approximately .16, which is lower because this marketing activity exerts an indirect effect.

Second, the results in Table 7 highlight the powerful role of investments in news quality in influencing subscription sales, which in turn drives advertising revenues. Indeed, the impact of news quality investment on advertising revenues is as large as the impact of ad space sales effort and somewhat stronger than its direct impact on subscription sales. This result is especially true in the small-firm segment, in which the average elasticities of subscriptions and advertising revenues with respect to news quality investments are as high as .57 and .64, respectively, which is significantly greater than the corresponding values in the large-firm segment, which are approximately .4 and .47. These differences between the two segments appear to be consistent with industry reports that the smaller newsroom staffs of smaller newspapers are used much more intensively than those of larger newspaper firms (Rosenstiel and Mitchell 2001). However the subscriptions–distribution and ad revenue–distribution elasticities in the large-firm segment are greater than those observed in the small-firm segment, perhaps because small-firm newspaper markets are closer to saturation with respect to distribution coverage than large-firm newspaper markets.

Diagnostic Tool for Assessing Under- or Overspending and Enhancing Profit

Although elasticity estimates are informative, they do not provide sufficient information about whether managers should actually increase or decrease investments in those activities from current levels. For example, for any magnitude of quality elasticity (large or small), it is prudent to decrease (increase) investments in quality if the newspaper company is located on the downhill (uphill) of the profit function (see Figure 1). Thus, to make profitable decisions, managers must know the firm's location on the profit function. To facilitate this goal, we present a diagnostic tool based on the following algorithm:

Step 1: For a given company i, derive the optimal decisions (q_i^*, d_i^*, a_i^*) as functions of the model parameters. Let $g_i(\theta)$ be a 3 × 1 vector-valued function of the vector of parameters θ.

Step 2: Draw 1000 samples $\tilde{\theta}_j$ from the normal distribution $N(\hat{\theta}, \hat{\Sigma})$, where $j = 1, \ldots, 1000$. This step accounts for both the magnitude of the estimates $\hat{\theta} = (\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_3, \hat{\beta}_1, \hat{\beta}_2)'$ and the uncertainty associated with them through their variance–covariance matrix $\hat{\Sigma}$.

Step 3: Evaluate the expressions in Step 1 using the realized parameter values in Step 2. Let $g_{ij} = g_i(\tilde{\theta}_j)$ be the evaluated quantities for company i at the realized parameter values in the jth draw.

Step 4: Sort the g_{ij} values in ascending order for each activity and locate the 25th and 975th values to obtain the lower- and upper-confidence limits ($\underline{x}_i$, $\bar{x}_i$), respectively.

Step 5: If the actual expenditure on an activity lies within its corresponding confidence limits ($\underline{x}_i$, $\bar{x}_i$), the investment decision for that activity is nearly optimal. If the actual expenditure is below $\underline{x}_i$, it represents underspending; if the actual expenditure is above $\bar{x}_i$, it represents overspending.

To derive the expressions required in Step 1, we maximize profit in Equation 3 subject to the demand system given in Equations 4 and 5. The resulting optimal decisions are

$$\begin{bmatrix} q_i^* \\ d_i^* \\ a_i^* \end{bmatrix} = \begin{bmatrix} \dfrac{m_{1i}k_i\alpha_2 + m_{2i}\alpha_2\beta_1}{1-\alpha_1\beta_1} \\ \dfrac{m_{1i}k_i\alpha_3 + m_{2i}\alpha_3\beta_1}{1-\alpha_1\beta_1} \\ \dfrac{m_{1i}k_i\alpha_1 + m_{2i}\beta_2}{1-\alpha_1\beta_1} \end{bmatrix} = g_i(\theta). \tag{7}$$

This five-step algorithm constitutes the diagnostic tool, which determines a firm's location on the profit function and enables managers to steer their companies toward optimality. To elucidate this point, consider a simplified situation in which a manager attempts to maximize profit (π) by changing invesxtment levels in quality (Q) and distribution (D). Figure 2, Panel A, locates Firm A on the profit function $\pi(Q, D)$, and Panel B shows its location in the decision

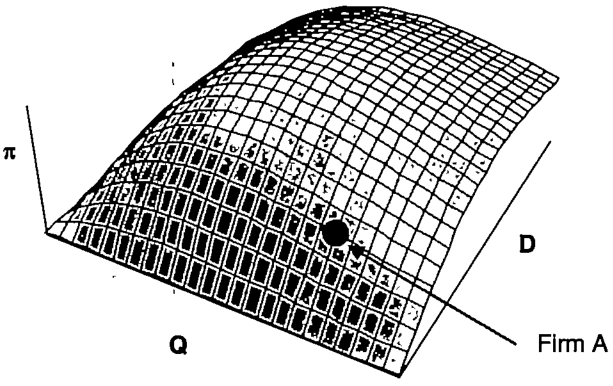
TABLE 7
Investment Elasticities

		1998		1999		2000		2001		S1	S2	Overall
Investment Elasticity	**Expression**	**S1**	**S2**	**S1**	**S2**	**S1**	**S2**	**S1**	**S2**	**Average**	**Average**	**Average**
Subscription with respect to advertising sales, $\partial Ln(S)/\partial Ln(a)$	$\frac{\alpha_1\beta_2}{S(1-\alpha_1\beta_1)}$	.10	.23	.14	.09	.18	.13	.19	.21	.15	.17	.16
Subscriptions with respect to distribution, $\partial Ln(S)/\partial Ln(d)$	$\frac{\alpha_3}{S(1-\alpha_1\beta_1)}$	.16	.30	.11	.32	.17	.23	.35	.20	.20	.26	.23
Subscriptions with respect to quality, $\partial Ln(S)/\partial Ln(q)$	$\frac{\alpha_2}{S(1-\alpha_1\beta_1)}$	.68	.33	.63	.48	.50	.40	.47	.39	.57	.40	.49
Ad revenue with respect to advertising sales, $\partial Ln(R)/\partial Ln(a)$	$\frac{\beta_2}{R(1-\alpha_1\beta_1)}$	.61	.54	.52	.41	.64	.38	.73	.50	.63	.46	.54
Ad revenue with respect to distribution, $\partial Ln(R)/\partial Ln(d)$	$\frac{\alpha_3\beta_1}{R(1-\alpha_1\beta_1)}$	.19	.35	.13	.37	.19	.28	.36	.22	.22	.31	.26
Ad revenue with respect to quality, $\partial Ln(R)/\partial Ln(q)$	$\frac{\alpha_2\beta_1}{R(1-\alpha_1\beta_1)}$	.76	.38	.76	.56	.53	.49	.49	.42	.64	.46	.55

Notes: S1 and S2 denote the small-firm and large-firm segments, respectively.

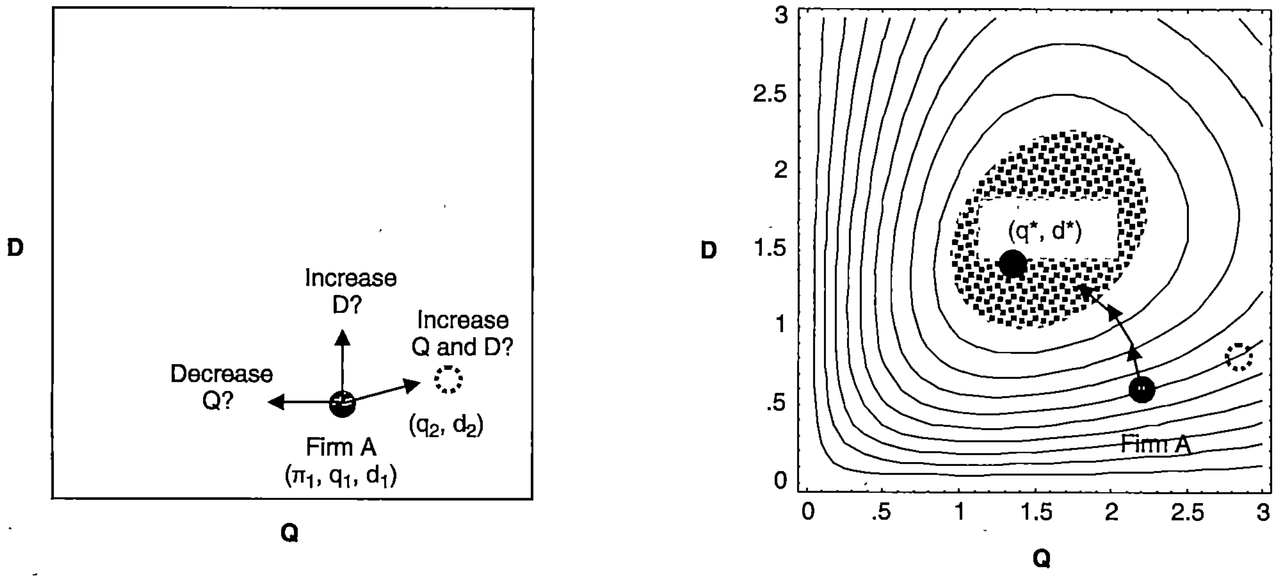
FIGURE 2
How the Diagnostic Tool Works

A: Firm on a Profit Function



B: Business Reality

C: Diagnostic Tool



space (Q, D). In practice, the manager does not "see" the firm on a profit function in the manner observed for Firm A in Panel A. Rather, as in Panel B, the manager knows only the invested amounts (q_1, d_1) and the associated profit π_1. In other words, the manager's business reality is the decision space in Panel B. This decision space becomes three-dimensional (or higher) when additional decisions must be made (as in the empirical study). In such cases, without analytic tools, it is impossible to "see" the profit function. Even if the simplified situation in Panel B is considered, should the manager decrease Q, increase D, or try some combination, for example, that increases both Q and D (see Panel B)? Such decisions move the firm to another location (q_2, d_2), which is shown by the dotted circle in Panel B, and this may or may not generate enhanced profit. Consequently, how should a manager's decisions be assessed in terms of whether they brought the firm closer to the optimal?

The proposed diagnostic tool provides this crucial information. Figure 2, Panel C, illustrates how the diagnostic tool works: First, it projects Firm A from its current profit level into the decision space; second, it constructs isoprofit contours in the decision space; and third, it identifies the optimal path to achieve the maximum profit. The shaded region in Panel C denotes the confidence region. Although the confidence region provides useful information on over- or underspending, it does not offer guidance to a manager to drive the firm from its current location into the neighborhood of maximum profit. This guidance comes from the optimal path that traces a perpendicular to isoprofit contours (see the curved arrows), which the diagnostic tool determines on the basis of the firm's current location on the profit function.

We used GAUSS Version 7.0 to code the tool. Applying this diagnostic tool to companies i = 1, ..., N (in each of the two segments across the four years), we generated the following empirical results: Averaging across years, Table 8, Panel A, displays the proportions of firms in each of the two segments that are located on the uphill side of the profit function (Type U for underspending), the downhill side (Type D for overspending), or near optimal (Type N) with respect to their current levels of investments in news quality, distribution, and advertising sales efforts. Table 8, Panel B, presents the year-by-year proportions of Type U, Type D, or Type N firms with respect to each investment variable in the two segments over the 1998–2001 period. (Note that when firms invest in multiple marketing activities, such as in our study, the typology of uphill, downhill, and near optimal refers to a particular investment decision by that company. That is, in practice, the same company can be underspending in quality, overspending in distribution, near its optimum spending on advertising, or some other combination.)

Focusing on Table 8, Panel A, we observe that the majority of the newspapers across the four years—more than 60% in the case of the small-firm segment and more than 80% in the large-firm segment—are Type N with respect to all three (q, d, a) investments. The higher propor-

TABLE 8
Proportions of Firms Underinvesting, Nearly Optimal, or Overinvesting

A: Average Across Years

Segment 1 (Small Firm)

	Type U: Underinvesting	Type N: Nearly Optimal	Type D: Overinvesting
Quality	22.1	68.7	9.2
Distribution	12.5	68.5	19.0
Ad sales	33.3	62.8	3.9

Segment 2 (Large Firm)

	Type U: Underinvesting	Type N: Nearly Optimal	Type D: Overinvesting
Quality	14.8	82.3	2.9
Distribution	11.5	85.4	3.2
Ad sales	14.7	84.0	1.3

B: Year by Year

	Segment 1 (Small Firm)			Segment 2 (Large Firm)		
Investments	**Type U**	**Type N**	**Type D**	**Type U**	**Type N**	**Type D**
1998						
Quality	28.5	71.4	.1	.93	98.14	.93
Distribution	.7	80.7	18.6	2.8	97.1	.1
Ad sales	1.5	80	18.5	6.5	93.4	.1
1999						
Quality	30.6	65.9	3.5	55.5	42.6	1.9
Distribution	.6	74.1	25.3	44.5	54.7	.63
Ad sales	17.1	77.1	5.8	26.1	71.3	2.5
2000						
Quality	8.2	84.4	6.3	1.5	97.6	.9
Distribution	.2	64.5	35.3	.7	92.9	6.7
Ad sales	29.7	67.08	3.16	6.2	92.9	.8
2001						
Quality	6.7	71.3	21.8	1.2	95.2	3.6
Distribution	23.4	58.8	17.7	1.2	94.1	4.7
Ad sales	51.5	45.3	3.2	24.7	74.1	1.2

tion of Type N firms in the large-firm segment implies that they may possess greater expertise in gauging marketing–sales response relationships. Next, when firms are suboptimal with respect to quality investments, they tend to be underspending rather than overspending. This tendency is more pronounced in the case of small-firm newspapers. Similarly, we observe that in both segments, the majority of suboptimal firms are underspending with respect to their advertising sales investments—specifically, 33.3% of the small-firm segment and approximately 14.7% of the large-firm segment. In contrast, in the case of distribution investments, we find that a greater proportion of suboptimal firms in the small-firm segment overspends rather than underspends. This finding reinforces our previous inference that small-firm's circulation–distribution investments are closer to the market saturation levels.

Table 8, Panel B, indicates that these patterns of results hold across the years except for 1998, during which a significant proportion of suboptimal firms overinvested in ad space sales efforts. This outcome may have arisen because some firms mistakenly assumed that they were operating in Market Type 4 when the market was actually Type 2 for the small-firm segment. We also observe that significantly greater proportions of companies in the large-firm segment were suboptimal (underinvesting) in all their marketing investments in 1999, which may be attributable to fears of an economic slowdown and recession-like conditions in 1999. In contrast, greater proportions of firms in both segments appear to have overinvested in news quality in 2001.

Summarizing the findings in Table 8, we observe that the two segments differ in their spending tendencies as follows:

Investment	Small Firm	Large Firm
Underspenders in quality	More likely	Less likely
Underspenders in distribution	Less likely	More likely
Underspenders in advertising	More likely	Less likely

These findings—that a majority of the newspapers in both the segments are Type N with respect to all three investment variables, and greater proportions of suboptimal firms with respect to quality and advertising sales investments are Type U than Type D—run counter to previous research results that characterize marketing managers as overspenders (e.g., Aaker and Carman 1982; Hanssens, Parsons, and Schultz 2001, p. 363; Prasad and Sen 1999). However, they lend support to and comport with the principles of economic theory that expect firms to behave optimally, especially in a 100-year-old newspaper industry in which many suboptimal firms would have disappeared. Moreover, the specific finding that the majority of newspapers are either nearly optimal or underspending with respect to quality substantiates Meyer and Kim's (2005, p, 7) conjecture that these companies—especially the smaller ones—are "clustered on the uphill" of the profit function with respect to news quality investments. Finally, the changing proportions of Type N firms across the years reveal that managers would find it difficult to know their companies' location on the profit function in the absence of the proposed diagnostic tool. Consequently, they risk making the serious errors in investment decisions we described in the beginning of this article, which, as industry analysts fear, would essentially lead to liquidating their firms (e.g., Rosenstiel and Mitchell 2004). The application of our proposed algorithm to locate their firms' positions on the profit function would assist them in making appropriate investment decisions (i.e., increase, decrease, or maintain the status quo) and thus steer their companies to regions of enhanced profitability.

Implications of Omission of Advertising Space Sales Carryover Effects

As we noted previously, to preserve the confidentiality of the data of reporting newspaper companies, the annual Inland data sets do not identify the individual newspapers in the samples or use a common case identification number for any newspaper company that reports every year. Indeed, the sizes (and, therefore, the composition) of the annual samples vary across the years, eliminating the possibility of longitudinal analyses and restricting us to annual cross-sectional analyses. Consequently, the proposed simultaneous equation response model does not explicitly allow for ad space sales carryover effects. However, despite this limitation, our research findings with respect to the effects and optimality of newspaper firms' ad space sales efforts remain meaningful for two reasons.

First, local newspapers' ad space sales carryover effect is likely to be weak. More specifically, the following characteristics of local newspapers' ad space selling (see, e.g., Niemesh 2004) suggest that these efforts have a high short-term impact but low carryover effects (e.g., Zoltners, Sinha, and Zoltners 2001, p. 75): (1) A high proportion of sales in each year arises from new, incremental business from many new customers with small purchase volumes and short selling cycles (typically three contacts); (2) the sales force is the primary and most important promotion vehicle; (3) the sales job calls for limited maintenance or service activity beyond overseeing the execution of a particular advertising project (ad space salespeople usually work with numerous clients and projects simultaneously); and (4) more than half of ad sales representatives' pay comes from variable pay (i.e., commissions and bonuses for meeting monthly sales quotas), suggesting a stronger and more immediate selling effort–sales linkage (Basu et al. 1985; Niemesh 2004).

Second, allowance for a significant sales effort carryover effect would not affect the directionality of either the related normative results in Table 1 or the empirical findings in Table 8, because the presence of this effect implies a larger profit-maximizing investment level than the short-term optimum. Indeed, our conclusion that newspaper firms tend to underspend with respect to the ad space sales effort would be reinforced. However, a worthwhile direction for further research would be to investigate the long-term effects of marketing investments in dual-revenue industries, such as daily newspapers, using appropriate longitudinal data when available.

Conclusions

Based on our analysis of the Inland Press Association data, the four key takeaways from this article are as follows: First, daily newspapers' dual revenues are interrelated with positive feedback effects; this is an assumption that several theoretical models make, but to date, it has been backed by limited empirical evidence. Second, investments in news quality affect not only subscription sales directly but also advertising revenues through subscriptions indirectly. This result is especially true for smaller-circulation newspapers whose newsrooms and editorial departments tend to be understaffed and overworked. Consequently, our answer to the question "Is good news quality good business?" is a resounding yes. Third, advertising revenues of both small and large firms respond positively to efforts to boost circulation directly (e.g., investment in news quality) as much as they respond to ad space sales effort. Fourth, investments in circulation–distribution also have significant direct and indirect effects on subscriptions and advertising revenues, respectively, though the strengths of these effects are not as great as those of news quality investments.

Collectively, these findings reinforce the value of marketing by establishing that marketing investments influence a firm's marketplace performance. More important, managers should recognize the assets that these investments build (see Rust et al. 2004). As we already mentioned, the NAA (2000) notes that delivery systems built by investments in circulation–distribution are significant, strategic assets. Similarly, investments in news quality and advertising sales enhance perceived quality and awareness, thus building brand equity, an invaluable marketing asset (see Keller 1998).

In general, this article examines and derives normative marketing-mix decision rules in dual-revenue markets with interrelated demands, thus generalizing Dorfman and Steiner's (1954) classic theorem and enriching the understanding of resource allocation across four different market types. Furthermore, the empirical analysis of the impact of marketing investments yields elasticity estimates, thus augmenting the sparse literature on quality, distribution, and personal selling effort elasticities.

Finally, as the title states, a key contribution of this article is the diagnostic tool, which is based on a simple five-step algorithm, that extracts information contained in the market data (on the responsiveness of readers and advertisers and their interrelated demands) and combines this information with the firm's knowledge of margins not only to recommend appropriate investments in quality, distribution, and advertising but also to identify an individual firm's location on the profit function to mitigate under- or overspending errors. In addition, it offers guidance by tracing the optimal path that drives the company from its current location to the neighborhood of the maximum profit (see Figure 2, Panel C). Recently, Sir Martin Sorrell, the chief executive of the world's largest ad agency, WPP Group, stated in a *Wall Street Journal* interview that "scientific analysis, including econometrics, is one of the most important areas in the marketing-services industry" (Patrick 2005, B8). The diagnostic tool we developed belongs to this genre of sophisticated econometric approaches. We hope that managers find it useful to enhance their firms' profitability.

Appendix A Derivation of the Optimal Investments in Quality, Distribution, and Advertising

Let (q^*, d^*, a^*) denote the three optimal investment levels, which exist when the profit function in Equation 3 is twice differentiable and its Hessian matrix is negatively definite over the set $\mathfrak{S}$, where $\mathfrak{S} = \{(q, d, a) \in \Re^3 | q > 0, d > 0, a > 0\}$. Furthermore, let π_x denote the partial derivative of profit with respect to variable x (x = q, d, a). The first-order conditions that maximize profit in Equation 3 are as follows:

$$\text{(A1)} \qquad \pi_q = km_1\frac{\partial S}{\partial q} + m_2\frac{\partial R}{\partial q} - 1 = 0,$$

$$\text{(A2)} \qquad \pi_d = km_1\frac{\partial S}{\partial d} + m_2\frac{\partial R}{\partial d} - 1 = 0, \text{ and}$$

$$\text{(A3)} \qquad \pi_a = km_1\frac{\partial S}{\partial a} + m_2\frac{\partial R}{\partial a} - 1 = 0.$$

To derive the optimal investment levels, consider the marginal effect of quality investments on subscriptions. Formally,

$$\text{(A4)} \quad \frac{\partial S}{\partial q} = \frac{\partial f_1}{\partial q} + \frac{\partial f_1}{\partial R}\frac{\partial f_2}{\partial S}\frac{\partial S}{\partial q} \Rightarrow \frac{\partial S}{\partial q} = \frac{1}{\delta}\frac{\partial f_1}{\partial q}, \text{ where } \delta = 1 - \frac{\partial f_1}{\partial R}\frac{\partial f_2}{\partial S}.$$

Similarly, the marginal effects of distribution and advertising selling investments on subscriptions are

$$\text{(A5)} \qquad \frac{\partial S}{\partial d} = \frac{1}{\delta}\frac{\partial f_1}{\partial d} \text{ and}$$

$$\text{(A6)} \qquad \frac{\partial S}{\partial a} = \frac{1}{\delta}\frac{\partial f_1}{\partial R}\frac{\partial R}{\partial a},$$

respectively.

Next, the marginal effect of quality investments on advertising revenue is given by

$$\text{(A7)} \qquad \frac{\partial R}{\partial q} = \frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial q} + \frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial R}\frac{\partial R}{\partial q} \Rightarrow \frac{\partial R}{\partial q} = \frac{1}{\delta}\frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial q}.$$

Similarly, the marginal effects of distribution and advertising selling investments on advertising revenue are given by

$$\text{(A8)} \qquad \frac{\partial R}{\partial d} = \frac{1}{\delta}\frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial d} \text{ and}$$

$$\text{(A9)} \qquad \frac{\partial R}{\partial a} = \frac{1}{\delta}\frac{\partial f_2}{\partial a}.$$

Finally, by substituting Equations A4–A9 in Equations A1, A2, and A3, we obtain the simplified first-order conditions:

(A10)
$$m_1k\frac{\partial f_1}{\partial q}+m_2\frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial q}=\delta,$$
$$m_1k\frac{\partial f_1}{\partial d}+m_2\frac{\partial f_2}{\partial S}\frac{\partial f_1}{\partial d}=\delta,\text{ and}$$
$$m_1k\frac{\partial f_1}{\partial R}\frac{\partial f_2}{\partial a}+m_2\frac{\partial f_2}{\partial a}=\delta.$$

The presence of $\delta \neq 1$ in Equation A10 makes these first-order conditions different from the standard ones obtained in single-revenue markets (e.g., Dorfman and Steiner 1954).

Appendix B
Mean and Variance of the Cross-Market Dependency Coefficient δ

We attempt to find the mean and variance of the random variable $\delta = 1 - \alpha\beta$, where $(\alpha, \beta)' \sim N(\mu, \Sigma)$, $\mu = (\bar{\alpha}, \bar{\beta})'$, and

$$\Sigma=\begin{bmatrix}\sigma_1^2 & \sigma_{12}\\ \sigma_{12} & \sigma_2^2\end{bmatrix}.$$

To find the mean, we use $\mathrm{Cov}(\alpha, \beta) = E(\alpha\beta) - \bar{\alpha}\bar{\beta}$ to obtain

(B1)
$$E(\delta) = 1 - E(\alpha\beta) = 1 - \bar{\alpha}\bar{\beta} - \sigma_{12}.$$

To find the variance of δ, we use a theorem from the work of Mathai and Provost (1992, p. 53) that states that

(B2)
$$\mathrm{Var}(X'AX) = 2\mathrm{tr}(A\Sigma)^2 + 4\mu'A\Sigma A\mu,$$

where X follows a multivariate normal distribution with mean μ and covariance Σ and A is a conformable symmetric matrix.

Next, we chose

$$A=\begin{bmatrix}0 & .5\\ .5 & 0\end{bmatrix}$$

and $X = (\alpha, \beta)'$ so that $\mathrm{Var}(X'AX) = \mathrm{Var}(\alpha\beta)$. Then, we simplify

$$(A\Sigma)^2 = (A\Sigma)(A\Sigma) = \frac{1}{4}\begin{bmatrix}\sigma_{12}^2+\sigma_1^2\sigma_2^2 & 2\sigma_{12}\sigma_2^2\\ 2\sigma_{12}\sigma_1^2 & \sigma_{12}^2+\sigma_1^2\sigma_2^2\end{bmatrix},$$

which implies that

(B3)
$$2\mathrm{tr}(A\Sigma)^2 = \sigma_{12}^2 + \sigma_1^2\sigma_2^2.$$

Similarly, it can be shown that

(B4)
$$4\mu'A\Sigma A\mu = \bar{\alpha}^2\sigma_2^2 + 2\bar{\alpha}\bar{\beta}\sigma_{12} + \bar{\beta}^2\sigma_1^2.$$

Finally, we combine the results of Equations B2, B3, and B4 to observe that

(B5)
$$\mathrm{Var}(\delta) = \mathrm{Var}(1-\alpha\beta) = \mathrm{Var}(\alpha\beta) = (\sigma_{12}^2 + \sigma_1^2\sigma_2^2) + (\bar{\alpha}^2\sigma_2^2 + 2\bar{\alpha}\bar{\beta}\sigma_{12} + \bar{\beta}^2\sigma_1^2),$$

thus furnishing the exact expression for the variance of cross-market dependency coefficient. This completes the proof.

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Kathryn A. Braun-LaTour, Michael S. LaTour, & George M. Zinkhan

Using Childhood Memories to Gain Insight into Brand Meaning

In this article, the authors introduce the concept that people's earliest and defining product memories can be used as a projective tool to help managers more fully understand consumers' relationships to their products. The authors use a study on three generations of automobile consumers to illustrate how these memories symbolize the consumer–brand relationship and how they can be used to gain insights into brand meaning. The findings indicate that people's earliest and defining experiences have an important influence on current and future preferences in predictable ways across the consumer life cycle. These memory experiences are symbolic to the consumer and represent a new lens for viewing brand meaning, which complements the toolbox of extant research methods. The authors provide details about this technique for managers who are searching for methods that recognize that consumers coproduce brand meanings.

Managers are always trying to find new ways to ask about what their brand means to consumers. An alternative way of phrasing this question is the focus of this investigation: What can consumers (and their memories) reveal about brand meaning? By identifying the development of the consumer self in relation to a given product or brand, marketers can uncover a powerful, emotional means of connecting (or reconnecting) their brand to consumers. Probing earliest memories (EMs) and defining memories (DMs) to understand personality and relationship issues is not new to either psychotherapists (e.g., Adler 1931; Bruhn 1985, 1990, 1992; Mosak and DiPietro 2006) or social psychologists (e.g., Bruner 2003; McAdams 1988, 2001; Singer 2001; Singer and Salovey 1993, 1996). Most theorists, from Freud to Jung to Piaget to Erikson (Csikzentmihalyi and Rochberg-Halton 1981), have recognized the importance of childhood in establishing relationships and "imprinting" preferences. In the academic marketing literature, however, the attention given to this topic has been relatively sparse, with only one study (that we are aware of) using a Freudian analysis of childhood experiences to provide insights into a present-day animalistic art collection (Holbrook 1988).

Within the consulting world, however, G. Clotaire Rapaille, the French-born anthropologist who studied under childhood development specialist Jean Piaget, has successfully marketed the importance of probing childhood memories. Rapaille has gained a reputation for his high-profile (and high-priced) studies that probe EMs. He does not publish his results in refereed journals and does not provide clients with documented analyses from interview sessions. His methods remain somewhat of a "secret," even though more than half of the *Fortune* 100 companies have sought his expertise at one time or another. Some may consider his theories somewhat dated and focus group sessions leading (Zaltman 2003). Nonetheless, Rapaille claims a series of successes (e.g., linking the importance of childhood associations to "Mom" and the smell of coffee brewing). It is reported that Procter & Gamble used, and continues to use, such information in its advertising campaign for Folger's (Hitt 2000). Rapaille's work with Chrysler resulted in the firm's strategy to bring back the original "essence" of the brand while incorporating new technology to design the popular PT Cruiser.

Some academics have been vocal in their opposition to Rapaille, claiming that his promises are too grand and his insights too simplistic (Sacks 2006). This article is not meant to be a treatise either in support of or in opposition to Rapaille. Rather, this article is motivated by a general interest in understanding how marketers can use consumer memories as a projective tool to understand what their product or brand means to consumers. The purpose of this article is to review the logic, development, and market uses for early memory elicitation and to demonstrate how EMs and DMs add insights into brand/product meaning for three generations of automobile consumers. The elicited memories can be interpreted on both literal and symbolic levels and can help marketers develop their own brand myths. Marketers who recognize that consumers coproduce brand

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meanings will find this method useful for their brand positioning and communication strategies.

Background

Methods and Meanings

When trying to understand the "whys" of consumer behavior, projective tools have been a popular choice of marketing researchers (for an extensive review, see Rook 2001). Projective methods represent a significant intersection of psychoanalytic theory, clinical psychology, social psychology, and cultural anthropology (Rook 1988).

As the name suggests, projective tools are tasks in which participants attribute to others what they cannot or will not see in themselves (McGrath, Sherry, and Levy 1993). The general belief is that people are neither able nor willing to provide data about themselves in a self-report fashion because of an ego-defensive reaction. A common feature of projective tasks is that they are relatively unstructured and lack transparency in that the participant cannot immediately determine the purpose of the test. The most well-known projective tests that have been applied in marketing are the Rorschach ink-blot test and the thematic apperception test (TAT; Rook 1988, 2001).

Sidney Levy (2003) and his colleagues at Social Research Inc. were among the first marketing researchers to embrace projective techniques. Among the many techniques Levy pioneered, the most relevant to this research is his work on storytelling and mythmaking (Levy 1981). Levy (1981) describes how consumer stories can be analyzed as projective, and he interprets such stories to explain consumption choices.

Although projective techniques (e.g., Levy 1981; Rook 2001) contribute important insights about consumer motivations, they tend to be static, telling where a person is now but nothing or little about the past or the intended future. Reed and Forehand (2003) propose that research is needed to understand the processes by which symbolic links between a brand and the consumer self are formed, and Aaker (1997) calls for greater understanding of how brand personalities develop. As Belk (1990, p. 674) notes, "self extends not only to the present material environment, but extends backward and forward in time." Thus, a technique that can capture the dynamics of the self has great promise for understanding consumer behavior.

The system that holds such information about the self and identity is called autobiographical memory (Conway and Rubin 1993), and it is the glue that provides consumers with a sense of continuity about the past, present, and future. Memory is a reconstructive process (Braun 1999; Schacter 1996) that never brings to mind an exact reproduction of the past but rather a recollection that is part fact and part fiction. "Autobiographical recollections do, indeed, enable us to bring to the present that which is past (memoria), but never the thing itself, only its reconstructed image in personal terms (fantasia), and always in the context of our continuously evolving systems of self-constructions (ingegno). In this way it is clear that constructive cognition spans the entire spectrum of the self, from the furthest reaches of our future anticipations and back as well into the deepest recesses of our recollections" (Neimeyer and Metzler 1994, p. 130).

We propose that consumers' autobiographies can provide marketers with memory stories that can be a projective tool for understanding consumers' thoughts and feelings about a product or brand. The logic for this method is based on the following ideas: First, autobiographical memory is the center of identity and contains memories of experiences that are the foundation for the self-concept (Baddelely 1988; Bruner 2003; Neisser 1981). Second, although autobiographical memory is self-centered, it also indirectly contains information about brands/products and the meanings they have added to consumers' lives (Hebridge 1988; Olsen 1995). Third, despite a lifetime of experiences, only a fraction are retained, so those that are remembered hold meaning (Bruhn 1985; Cohen 1989). Fourth, the more distant (i.e., "earliest"; Bruhn 1990, 1992) and more repeated (i.e., "defining"; Singer and Salovey 1993) experiences are more likely to become myths and reveal important symbolic meanings about the product/brand. According to Zaltman (2003, p. 213), "Many consumer memories are archetypes, defined as images that capture essential, universal commonalities across a variety of experiences."

There are two streams of systematic research that focus on autobiographical memories as projective techniques that parallel the developing consumer self. One stream, which originates in Alfred Adler's individual psychology, explores how EMs provide the stories that guide people's lives and become part of people's identities. These memories, which are rooted in early childhood, contain emotional and symbolic meaning. The other stream emerges from sociocultural and narrative practice theories. This research explores the role of DMs in the development of personality, particularly during adolescence. The current research is situated in the confluence of both these streams.

EMs

The EM method is one of the first projective techniques used by psychoanalysts, and it predates the Rorschach and TAT by many years (Mosak and DiPietro 2006). This technique was pioneered by psychologist Alfred Adler, who viewed his patients' EMs as important because they represent a person's subjective starting point in his or her autobiography and reveal the first symbol of the self (Adler 1931). To Adler, these memories provided a blueprint as to what sort of person one becomes and also forecasted the types of experiences a person might be likely to encounter later in life. The EM a person recalls is important because it sets the stage for what happens next—a string of associations linked by the larger theme of "what is important to me right now." Psychotherapists have been using the EM procedure for more than 80 years, and Bruhn (1992, p. 13) posits that "we recall incidents that mirror and substantiate our current perceptions and beliefs and 'overlook' or 'forget' incidents that are inconsistent with present beliefs."

The premise is that EMs operate as a projective technique based on the errors that are inherent in the memory and retrieval process. The focus is on patients' recollections of specific incidents that occur before the age of ten. To keep their memory stories coherent, people fill in the missing parts of the stories that their memories cannot finish. They project themselves—personality and lifestyle preferences—into their EMs. Therefore, there is a mythic element to the EMs, which enables them to be interpreted not only at a literal level but also at a symbolic level. Myths are prose narratives that are considered truthful accounts of what happened in the remote past. The people telling the memory story may not be aware of how their memory has been shaped by their own personality, needs, biases, and so forth. As a result, EMs are not transparent, similar to the projective methods that marketers traditionally use. Nonetheless, participants reveal more about themselves through their memories than they might initially think, partly because they are not aware of how such memories have been shaped (see Mosak and DiPietro 2006).

Although most psychoanalysts use childhood memories as part of their therapy, Bruhn (1990) laments that there has been a lack of leadership and systematic follow-through in the development of EMs and their usage beyond that setting. The cognitive psychologist Ulric Neisser (1982) cites EMs as a promising but virtually unexplored area. The Adlerian view of the importance and usage of EMs has been limited primarily to psychotherapists, who use them as an important tool for understanding patients' present-day concerns. They have been used to predict future events, such as the success/failure of a marriage and vocational choices, and they have been used retrospectively to understand the differences in childhood between delinquents and nondelinquents (Mosak and DiPietro 2006).

Autobiographical Memory, Narrative Development, and Childhood Attachment

> One of my discoveries was that in order to create the first imprint of a word—when you learn a word, whatever it is, "coffee," "love," "'mother," there is always a first time. There's a first time to learn everything. The first time you understand you imprint the meaning of this word; you create a mental connection that you're going to keep using the rest of your life. And to create this mental connection, you need some emotions. Without emotion, there is no production of neurotransmitters in the brain, and you don't create the connection. So actually every word has a mental highway. I call that a code, an unconscious code in the brain. (Rapaille 2004)

It is not clear that Rapaille "discovered" childhood imprinting, but he has a valid point with regard to the importance of early exposure. Bowlby (1982) and other psychological researchers argue that there seems to be a "sensitive" period during which mother–child attachment forms. "Attachment" is an inborn system in the brain that evolves in ways that influence motivational, emotional, and memory processes with respect to significant others (Pillemer 1998). This system motivates a child to seek closeness with his or her parents and to communicate with them. These experiences with others become encoded into implicit memory and serve as expectations that help children find their "secure base." During the developmental period in which most EMs occur, children actively seek out attachment relationships. Research suggests that these attachment patterns affect interpersonal relationships later in life (Harzan and Shaver 1987) and even influence the nature of the type of relationship a person has, for example, with a car dealer (Fournier and Paulssen 2005).

What may be more relevant to autobiographical memory is the relationship between the brain and storytelling. According to Damasio (1999, p. 30), "Consciousness begins when brains are given the power, the simple power I must add, of telling a story." Young children learn how to develop a life narrative from their parents. Social cognitive psychologists have proposed that autobiographical memory emerges after the appearance of language (Nelson 1993). Children begin to talk about past events at around two years of age, and their ability to engage in memory talk about past events develops rapidly during the third and fourth years.

Psychologists have come to realize that the complex mixtures of personal knowledge that are woven together to form autobiographies and personal myths are a function not only of individuals but also of their culture. Throughout the school years, children's memories are shaped by the narrative style their culture espouses. Their experiences are grafted onto the meanings and markers of that culture. "[T]the culture a person grows up in strongly influences his or her brain's 'wiring,' or neural pathways, in the early years of life. The stories we hear starting in early childhood become important frames of reference or mental models that later influence the products and brands we buy, especially if stories about those brands resonate with deep cultural meanings embedded in our memories" (Zaltman 2003, p. 192).

DMs

There are other important points in the development of the consumer self that are likely to influence consumption behavior. Erikson (1968) points to adolescence as an important period of identity development during which questions such as "Who am I?" and "How do I fit in?" are typically raised. For visible products, such as automobiles, social influences may be more important than familial or personal factors in determining choice. Historically, cars have eclipsed most other objects as a means of self-awareness and of knowing about others (Marsh and Collett 1986). Cars can mediate social relationships indirectly, through symbols, and directly, through the capacity to serve as a common focal point of attention (Collins 2000). As the self becomes more unified during adolescence (Erikson 1968), social networks become broader and offer many opportunities to communicate the self through conspicuous consumption activities. As Belk, Bahn, and Mayer (1982, p. 10) note, "This may suggest that age and sociability inferences based on consumption cues are strongest during adolescence." Researchers on nostalgia (Holbrook and Schindler 1991, 1996) find that adolescence is the period when consumers learn their preferences for culturally observable products (e.g., films).

Social psychologists have begun to investigate DMs as a means to uncover personality traits (McAdams 1988, 2001; Singer and Salovey 1993). Their focus has not been on the age of memories but rather on memories that share the characteristics of affective intensity, vividness, repetitiveness, and linkage to other memories (Singer and Salovey 1993). The more memories are repeated and shared with others, the more opportunities there are for reconstructions and alterations (Bartlett 1932), which makes DMs also likely to contain mythic elements. For automobiles, we expect that most DMs come from participants' adolescence because that is the time people typically remember more information about their lives (called the "reminiscence bump"; Schacter 1996). Indeed, Belk (2004) finds that many of his participants' fond recollections of automobiles came from this period.

As with EMs, DMs can serve as important symbolic experiences that can be used as a projective device. For example, Singer and Salovey (1996) find that life goals and motivations are revealed through DMs. As an example, Singer (2001) uses DMs to provide insight into the motivations of a heroin addict. In general, these memories are linked to the present emotional state of the person. Moffit and colleagues (1994) find that depressives have more negative DMs than nondepressives. McAdams (1988) finds that personality traits, such as power and intimacy, are reflected in certain types of DMs. As have EMs, DMs have been used by clinical psychologists as a focus of intervention in both individual and couples psychotherapy. In addition, they provide important opportunities for lesson learning and meaning making that contribute to a person's sense of purpose and identity.

Childhood Memory Elicitation Method

As do other projective techniques (i.e., the TAT; Rook 1988), the methods used in psychotherapy and counseling need to be adapted for the consumer-market situation. For example, although EMs and DMs may provide much insight about an individual in a counseling session, marketers are interested in what the product means to the consumer. There are issues regarding whether the childhood memories revolve around brands, products, or product types. Whereas psychotherapists might have years to probe and understand patients' childhood memories, marketers need results much quicker.

We began the development of a consumer EM and DM projective technique based on two very different approaches: (1) the EM and the DM questionnaires (see Bruhn 1990; Singer and Salovey 1993, respectively) and (2) Rapaille's focus group–type setting. The latter (according to a PBS *Frontline* interview in "The Persuaders" miniseries; see Rapaille 2004) consists of a four-hour group session that is divided into three parts. The first part is a typical focus group that allows participants to rationalize and discuss their thoughts about a brand. The information from this part is usually discarded. After a break, during which participants reportedly "feel good" about their intellectual contribution, they come back for a second session and are asked to tell emotional childhood fairy tales to Rapaille about the product (according to Rapaille, this is to confuse them). In the third session, after another break, participants come back to a dimly lit room in which their chairs have been replaced by pillows and blankets; they are asked to lie down on the floor in a fetal position and relax. Some memory cues are provided, and participants are asked to either write down or discuss their EM of the product. According to Rapaille (2006), people regularly report that during these sessions, memories come back to them that they had forgotten for years.

The questionnaire method asks people to write down their EM ("a specific happening or event from your childhood, an event that you actually remember, and a one-time specific incident occurring under the age of 10") or DM ("has to be at least one year old, something that you remember very clearly, a memory you would tell someone else if you wanted that person to understand you in a profound way"). Next, participants are asked to write down when it occurred, what was the clearest part of the memory, what was the strongest feeling in the memory, and what thought or action is connected to that memory.

Because of the importance of surfacing a singular representation for the EM before the age of ten (Bruhn 1990) and the difficulty some people have recalling EMs (Mosak and Pietro 2006), we combined aspects of both techniques in our development of the memory elicitation procedure. Participants are told beforehand that they will be participating in a memory exercise about their childhood and to feel free to prepare by looking at pictures or talking to family members before the study. At the time of the study, they are directed to sit on the floor on a comfortable blanket. The researcher begins with several yoga warm-ups both to "break the ice" and to get participants in a more relaxed physical state. Autobiographical memories are more likely to be accessed in a calmer, less active state of mind (LeDoux 1996). Next, the researcher leads the group through some breathing and visualization exercises and then takes them through a "memory walk," in which he or she provides some landmark cues and leads them back in time to their childhoods. This approach is based on the hierarchical structure of autobiographical memory (Barsalou 1988). The highest level of abstraction involves landmark events (i.e., national and cultural happenings that pinpoint a moment in time rather than specific years or dates). The other levels—life themes, generic action events, and emotion/sensory images—were not mentioned in the memory walk because we wanted participants to fill in these details with their own memory stories.

When the researcher gets to participants' earliest childhood, he or she asks them to write down or draw images associated with their EM of the product/brand. (McAbee and McAbee [1979] find that drawing EMs is a valid method for helping clients recall information.) Then they are told, "close your eyes and imagine a time when you had an experience with a brand/product and that defined that brand/product for you (pause), what you learned what that brand/product was like through this experience (pause); it portrayed a certain personality to you (pause), and you portrayed a certain personality to the world in this brand/product (pause); bring that experience to mind." Participants are then allowed several minutes to write down words and images associated with that experience. After the memory-walk session, they are given a questionnaire that asks them to write a story about each of the memories and to answer a few questions about it, such as, "How old were you when this experience took place?" "What is the most vivid part of the memory?" and "What emotion did you feel as you experienced the event?"

Before and in preparation for our main study, we conducted pilot studies on EMs and DMs using the previously described methods—one for Coca-Cola (Braun-LaTour, LaTour, and Zinkhan 2005) and the other for an automobile manufacturer (Braun-LaTour 2001). In the Coca-Cola study, we found that even for an iconic brand such as Coke—we conducted this study with participants from the Deep South who (literally) were served Coke in their baby bottles—participants' memories were more easily accessed at the product (not brand) level. In that study, we asked participants to write down their EM and DM before the main session, and we compared them with the memories that were elicited in the main session; we used questionnaires similar to those that psychoanalysts and social psychologists use. We found that the DMs did not vary much, but we found many more singular memories and EMs when participants went through the relaxation and memory-walk session (though the general themes did not differ). This is consistent with findings in the literature. For example, Usher and Neisser (1993) were able to get people to remember events as early as age two with their targeted techniques, whereas most EM researchers report an average age of three or four when using a questionnaire (Kihlstrom and Harackiewicz 1982). For adults, it is easier to recover memories from late adolescence than to recover memories from early childhood because it operates with the same autobiographical memory system (Kotre 1995). As did Rapaille's respondents, many of our participants reported remembering things from childhood that they had not thought about for years after the memory elicitation session.

In the automobile study, we explored whether people would tell longer and more involved stories if they were recorded with a camera than if they were simply asked to write down such stories on a questionnaire. We found that people were much more willing to tell their stories to a camera than to write them down. This method also offered an opportunity to probe the memories for more details, linkages to other experiences, and so forth. Note that Bruhn (1990) and others (e.g., Mosak and DiPietro 2006) believe that several memories may be needed to identify life themes, so this superficial questioning (five to ten minutes per participant) helped draw out such connections. Allers, Katrin, and White (1997) compare tape-recorded EMs to written EMs and find significantly more words and more self-references in the tape-recorded versions (though about the same amount of projective material). Written EMs may be less nuanced because participants may omit feelings or vivid details.

The pilot studies resulted in three adaptations to our initially contrived memory session. First, we learned that we would best be able to access memories at the product level. Second, we recognized that the relaxation/memory walk was an important component of the exercise and should be retained because of the greater quantity of singular memories and EMs. Third, we found that videotaping and superficial questioning of the memories would yield more detailed and vivid accounts than written memory stories.

Modes of Analysis

Interpreting the EMs and DMs is like detective work; it is a process of searching for meaning (Levy 1981). The memories can be examined on two levels—the more literal, content level or the mythic, deeper level. The content level involves coding the memory stories and quantifying them on various dimensions, such as age when the memory took place, whether it was a singular or a recurring event, whether it involved close family members or an extended social circle, the emotions associated with the memories, themes in the memories, and generic events featured in the memory stories. According to Mosak and Di Pietro (2006), there was a group of researchers who sought to quantify aspects of the EMs, but this led (in their opinion) to superficial analysis of the memories. This viewpoint is congruent with what Levy (1981) observes in his different levels of analysis of the narrative form. Therefore, we code for these aspects not only to get an overall impression of the memories but also to go deeper in the analysis.

To interpret the memory stories as myths, it is necessary to be able to read and interpret the metaphors and symbols in the stories, make comparisons across individuals (within the culture) regarding their stories (e.g., significant characters, events, actions), and learn and understand the culture that produced the myth. Observing how participants project themselves and their feelings about cars into their memory stories through their choice of incidents, language, emotional tone, and logic is of foremost interest (Levy 1981). Such approach is similar to the hermeneutical approach to consumer narratives (Thompson 1997) in which the stories are viewed as expressing existential themes by which a person's self-identity is reflected and as drawing from a cultural code of shared historical meanings and viewpoints.

In Rapaille's approach to interpreting memory stories, he focuses on structural elements, especially on the verbs used (Woll 2001), rather than the content. For example, when considering participants' memories of automobiles, he is more interested in the relationship between the person and the car than whether one story takes place in the city and another in the country. This is related to Jung's ([1919] 1970, ¶ 53) view of the archetype as action or image: "Archetypes are systems of readiness for action, and at the same time images and emotions. They are inherited with the brain structure—indeed they are its psychic aspect." Samuels (1985) argues that archetypes can be found in everyday experiences. Rapaille's goal is to find the archetype or "the code" for the product, which is typically described as one word, for example, "car = identity." Rapaille (2004) claims that each product has an enduring archetype, and different age groups within the same culture should not differ in their expression of that archetype. Rapaille's interpretation of the memory stories is similar to what Zaltman (2003) proposes when looking for deep metaphors. Deep metaphors are the home for latent and emerging needs and the source of basic perceptual and behavioral predispositions. The importance of deep metaphors is reinforced by contemporary work in neurobiology and cognitive linguistics pertaining to embodied cognition (Zaltman 2003). According to Zaltman (2003, p.

14), archetypes and deep metaphors are often one and the same. As universal patterns or motifs that come from the collective unconscious, archetypal images are the basic content of religions, mythologies, legends, and fairy tales (Hirschman 2000).

The Study

Automobile memories are the focus of our study. We chose this product category because it has been heavily researched in the self-concept literature and provides an opportunity to build on this prior research (for a thorough review, see Belk, Bahn, and Mayer 1982).

Our sample came from the southwestern United States and included 60 participants who represent three age cohorts: 20 13ERs, or Generation Xers, between the ages of 25 and 35 (10 male, 10 female); 20 baby boomers between the ages of 40 and 55 (12 male, 8 female); and 20 participants from the silent generation (or pre–baby boomers) ages 65 and over (12 male, 8 female). A professional market research firm recruited these people to participate in this study. Each was paid $100 for their participation (more if they completed a depth interview the next day). The interviews were conducted during the spring of 2002, a year after the PT Cruiser was introduced (and was a huge success), the year Ford Thunderbird was released (with much anticipation), and amid rumors of the Ford Mustang being reintroduced. It was shortly after September 11, and fear was still abundant in this large metropolitan city in which driving has always been an important part of life. Retro cars were hot, and so was retro advertising. The "crossover" vehicles (e.g., the Escalade, the Hummer) were not yet introduced.

Heterogeneity among consumers' personal histories can frame their perceptions of their needs in different meaning systems (Thompson 1997). In his research, Rapaille has typically considered differences across countries when considering cultural differences in imprinting. However, we focus on three generations of Americans. According to Strauss and Howe (1991), each generation has its own personality or viewpoint from which it approaches automobiles. For example, the silent generation is more "other directed" and adaptive; the baby boomers are more idealistic, filled with optimism and hubris; and the Generation Xers were the most neglected and looked down on. In addition, each generation grew up during a period that advocated different types of parental roles. The silent generation was told to obey and be quiet and were overprotected by their parents; baby boomers were the most spoiled, having mothers at home and being the most nurtured and most relaxed; and Generation Xers had parents who were more distant toward them and underprotected them. Because parental involvement is so important for the development of childhood memories, we expected this to influence the type of memories elicited. Each generation also grew up in a different cultural environment, with different models of cars, different types of landmark events, different wars, different movies, and so forth. We were interested in whether the age cohorts would exhibit similar or different types of EMs and DMs (e.g., Belk, Bahn, and Mayer 1982). We expected different types of car models and historical references to be of importance across the different cohorts, but we were also interested in similarities in the types of experiences (and their underlying metaphors/archetypes) they discussed. Whereas Rapaille believes that the cultural imprint should not vary among age groups, we believed that the cultural environment in which our sample grew up was so vastly different that there would be differences. In addition, this sample enables us to examine how different types of memories affect decision making across the consumer life cycle.

Procedure

Participants were recruited over the telephone and were told the following:

> We're interested in hearing about your childhood experiences with automobiles. We're asking you to participate in a memory journey exercise where we will help you remember past experiences by giving you cues and providing memory guidance. In order to prepare for your journey, we'd like you to begin thinking about your childhood and experiences that you associate with cars. For instance, you might consider looking at a photo album or talking to family members about your childhood. We are particularly interested in childhood memories, memories of experiences that occurred to you early in life (under age ten); however, if you have a particularly important memory that occurred later, you might start thinking about what that memory means to you.

Note that such instruction "primes" them for the main session and enables them to benefit from "hypermnesia" (Schacter 1996), a finding in the memory literature that when a person is given a task, such as remembering people in his or her high school class, the person is able to remember more and more over time because of the consolidation processes in the brain. In addition, researchers (e.g., Zaltman 2003) have found that providing "homework" material before the session leads to more engaged participants.

The three age cohorts were run in separate groups. The main session followed the same format we described previously, beginning with a relaxation session, then turning to the "memory walk" back in time, and then focusing on the EMs and DMs. Participants received a written questionnaire in which they wrote their memory stories and answered questions such as, "How old were you when the experience took place?" "Where did the experience take place?" "What is the clearest part of the memory?" "What is the strongest feeling in the memory?" "If you had to put a title on this memory, what would it be?" "What role did the car play in this memory?" and "If the car could talk, what would he or she say about this experience?" They were also asked to write down what personal and cultural events were occurring around the time their memory took place. Participants were taken one at a time to another room in which they were asked to relate both their EM and DM memory stories to the researcher. The researcher asked them some questions about their memories, prompting them for details such as when, where, and with whom the experience took place to help them develop a richer narrative. When appropriate, the researcher asked whether those experiences affected the participants' current choices or decision making for cars at other times in their lives.

At total of 15 participants, 5 from each age cohort, were selected to come back the next day for a depth interview about their memories. That interview lasted approximately 90 minutes. Participants were asked to bring pictures or images that represented their EMs or DMs. This interview was structured similar to a Zaltman metaphor elicitation technique (ZMET) interview in which the participants' memory pictures are used to guide the interview (Zaltman 2003). In general, pictures/collages have been used to help guide personal interviews (e.g., Belk, Bahn, and Mayer 1982). For example, participants were asked how the pictures related to their memory, to tell their memory story again, what images/emotions came to mind, who was involved in the memory, what else was happening to them during the time the memory took place, why they thought they remembered that particular event, what they learned from that experience, what the next memory that came to mind was, and so on. The reason for conducting these one-on-one interviews was to determine whether the EMs and DMs elicited during the session would yield insights into brand and product meanings beyond those experiences.

Coding

In total, there were 60 EMs and 60 DMs elicited from participants. We used the transcripts of the videotaped sessions, not the written memory stories, for the analysis (though we checked to make sure the stories were the same). The transcripts of the depth interviews provided additional material about how the EM and DM influenced other aspects of the participants' lives. These stories and interviews provided a framework for understanding consumers and their developing relationship with automobiles. The interpretation of the memory stories was discovery oriented (Wells 1993). For the analysis, we used two coders who were trained extensively in qualitative data interpretation. We used an extensive, structured process to identify the key themes (as per Dey 1999; Spiggle 1994), or what the memory literature might deem as "generic events" (defined as the basic action taking place in the story, such as going fishing). They also coded whether the event was singular or recurring, the participant's age during the experience, the emotion of the memory, and who was involved. In addition, the stories were examined for structural similarities (within and between generations) to identify myths (and potentially the archetype or "code").

Results

The purpose of this section is to illustrate how managers can use the EM and DM data. We begin by describing the different properties of the memories (e.g., average age, type of events, emotions); then we create a memory network map, which is drawn mainly from our depth interviews but also incorporates comments participants made during the videotaped sessions. This map defines areas in which the EMs and DMs can lend the most insight. It also identifies the tension or struggle within this product category, which is the basis of mythmaking. Each generation dealt with the tension differently, and this led to different myths. Thus, we discuss them separately.

EMs

The average age at which the EMs occurred was six. This stage is what Piaget (1952) classifies as the early preoperational period and is a time when all components of the autobiographical memory system are in place. Research suggests that people have already learned symbolic meaning and brand status by this time in life (Hite and Hite 1995), and self–brand connections are in a state of development (Chaplin and John 2005). Across generations, the EMs stood for similar notions; some of the major aspects involved in the EMs included family car, excitement, safety (physical and emotional), bonding, comfort, and fun. Of the EMs, 80% were for single experiences (and almost all the Generation Xers had singular EMs and showed the strongest relationship between that memory and their current car choice). For example, the following is Generation Xer Tom's memory of a singular event that influenced his later preferences:

> When I was about four years old, I remember going to the beach in my dad's Toyota truck. The day stood out because it was my birthday, and my dad took off work to bring me to the beach. I can smell and taste the saltwater breeze mixed with the exhaust of this off-road machine, and to this day, I have a fascination with Toyota trucks. Ever since I was brainwashed as a child with this love for Toyota trucks, I have been a definite consumer of this brand name. My personal consumer memory has almost forced me to only want this type of vehicle. Since I have been able to work and drive, I have owned three Toyota trucks.

We used the recurring memories for the analysis as well. They contained similar themes and content as the singular EMs. What they lacked was detail.

The categorization of memories into general action events resulted in the following experiences: weekend family outings or special outings with a parent, birthday parties, family vacations, visiting grandparents or other relatives, and "pretend" driving on a parent's lap. It was noteworthy that most of these experiences were family oriented and associated with feelings of attachment. As we discussed in the "Background" section, children actively seek out attachment relationships during this time of their life. Thus, it is not surprising that the majority of EM was concerned primarily with the need for attachment—seeking to be with family to share and relate experiences together. Cars were viewed as an essential part of family life and were associated with bringing joy and family unity (Rapaille 2006).

In the EM experiences, the car played the role of bringing family members together. The car was either stationed at home or involved in transporting members to and from their homes. Furthermore, although DMs included people other than close family members, the focus in all the EMs was on family. No external actors were present.

The EMs represented feelings of "emotional safety," which is a safe psychological bond with family members. For example, Marisa, a Generation Xer, described her uncle's car as like "being in a living room" where it was comfortable and where she felt safe and warm. Another respondent described the family van as being "home" and containing all the person's toys and junk.

Positive EMs reflect wishes, what people return to again and again. The following silent generation memory demonstrates how even in the most depressing situations, the car acted as comfort and provided a "homelike" container: Alan recalled being at his father's funeral and was surprised by how comfortable he felt in the limousine, noting that he was as comfortable as being in a large chair in his own home. Several participants remarked on the size of the family car and its comfort.

The emotion involved in these memories was a feeling of safety, of being cared for and comforted. The psychotherapist Donald Woods Winnicott ([1958] 1965), best known for his "transitional object" theory (i.e., security blanket), finds that EMs that bring a feeling of being warm and snug tap into how a patient experiences security, emotional comfort, and basic ego relatedness. By extension, it is possible that these EMs could represent the components of "mothering" as portrayed in the transitional object. Such an object enables the child to have a fantasized bond with the mother as she gradually separates for increasingly longer periods of time. In adulthood, the EM represents a way to reconnect to that feeling of being cared for.

In addition to exploring the role of the participants and what they experienced, another important issue is the role of the car in the memories. Is it a passive observer? Is it central to the action? What sort of "personality" does it reveal? In both types of memories, the car played a central role. As we discussed previously, the car's role in the EM was that of connecting family members. The survey asked participants what they believed the car would "say" about their experience if it had a chance (Cooper 1974); some of those responses were, "Let's go, happy wanderers" (baby boomer); "I am glad that I provided your family with everything I could" (silent generation); and "Look how happy they are" (Generation Xer).

Participants also had an opportunity to list the personality traits associated with their EM car. One participant said that the image of the Chevron car, with a smile on its front, came to mind. The following are some of the adjectives they chose: "jovial," "happy," "comfort," "fun," "reliable," "motherly," "dependable," "staid," "sturdy," "calm," "steady," "trusting," "gentle," and "strong." Finally, participants were asked what, if any, aspects of their EM car they would like to see on cars today. They responded with words such as "reliable," "dependable," "comfort," "family friendly," "simple," "solid," "strong," "roomy," and "safe." Note that these are traits that consumers look for when selecting a "family car" to purchase. The brands or products they most associated with their EM were Jeep, Grand Torino, Volkswagen bus, van, Chevy Bel Aire, Cadillac, Buick, station wagon, sedan, and minivan.

DMs

Whereas the EM experiences centered on families, the DMs showed the influence of external members of the participants' social circles. These memories featured the ideas of "showing off," "going for a joy ride," the car being an expression of "me," and desire for status. Of the DMs, 60% were for singular experiences. Many combined experiences together, such as "riding in a convertible." Neisser (1981) dubbed such memories as "repisodic" because they appear as constructive amalgrams of repeated episodic memories.

We found that 14 was the average age when DMs occurred. Piaget classifies consumers at this age as being in the formal stage of operations. People who reach the formal operation stage are capable of thinking logically and abstractly. Defining memories included people, socialization, learning, life, school friends, and new cars. The following generic experiences were associated with the DMs: learning how to drive, pride in owning a car, admiring another person's car, driving in a "cool" car (and enjoying being admired), and going for a joy ride. The majority of these experiences are related to purchasing or being directly involved with the car. The car enabled the consumer to define him- or herself to others. Emotions, such as pride, were involved. Consider Mary's (a baby boomer) statement:

> My dad bought a new 64 Pontiac Grand Prix. It had leather interior and awesome air conditioning.... Our last car did not have either. It also had wood grain.... I felt like we arrived. I even got into an argument with my friend, saying that it was more prestigious than his parent's Lincoln Continental, but of course I was wrong.

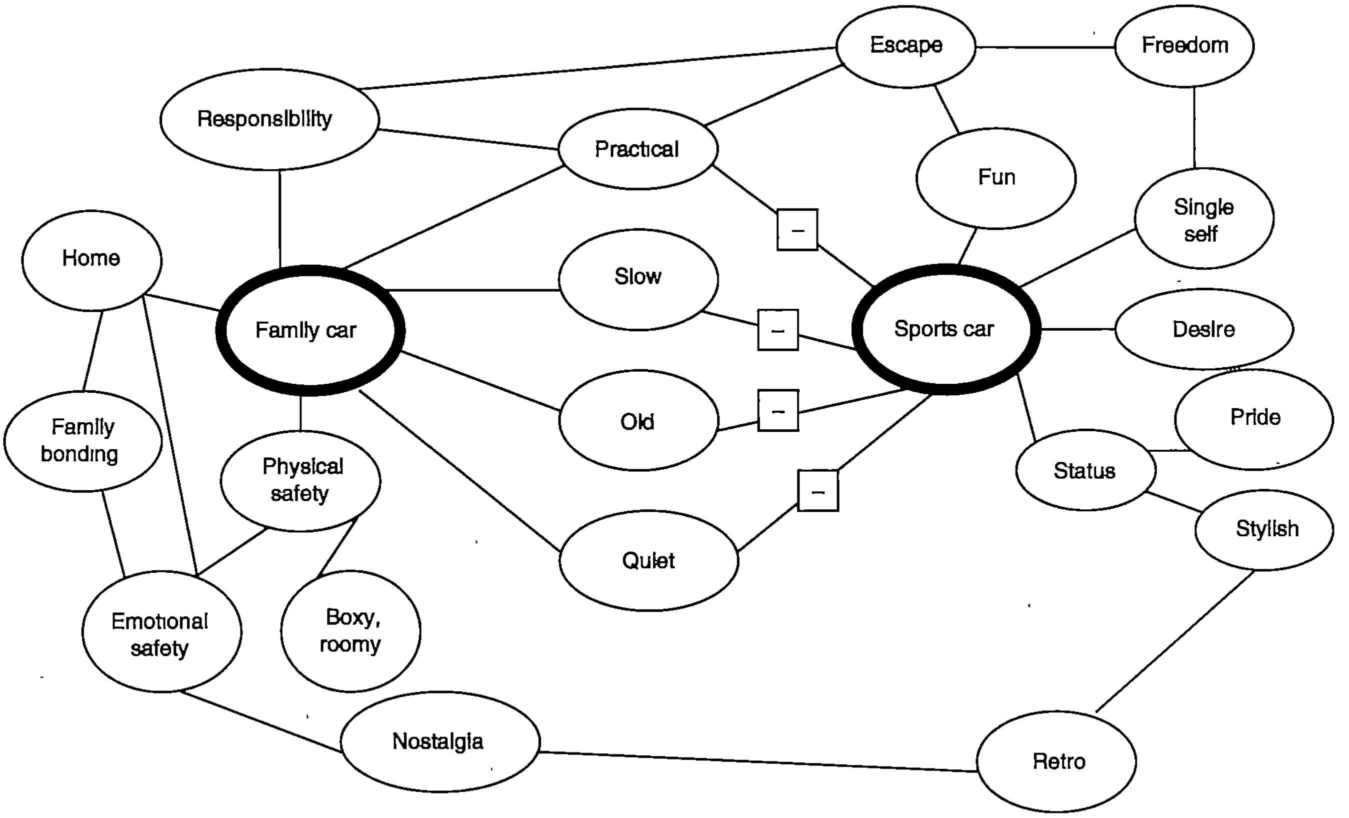
The car was a means to "show off" or impress. Note that there is also a level of vulnerability here or a need for approval. Steve, a baby boomer, related that his Porsche 914 was the epitome of "sophistication and cool" and that women were really impressed. In his research on male enthusiast drivers, Belk (2004, p. 247) finds that men often view cars as a "magical sexual charm that will make them irresistible to women." The car was viewed as a symbol of success and accomplishment. Likewise, Generation Xer Mark remembered that he and his best friend both had Nissan Z cars and called themselves "Z-men," and that made him feel special, as if he had accomplished something.

The defining car was something to be experienced, enjoyed, and shown off. The following descriptions are what people noted that the car would say about their DM: "Let's rock" (baby boomer), "I lived my 15 minutes of fame" (silent generation), and "I took you folks on the ride of your life" (Generation Xer). Participants described their brand-defining car as having the following personality traits: "fashionable," "sexy," "cool," "image maker," "fast," "proud," "attractive," "classy," "fun-loving," "outgoing," "macho," "almost uncontrollable," and "smooth." Desired qualities from the defining car were "luxury," "sexy," "speed," "convertible," "expensive," "fast," "cool," "reputation," and "styling." The brands or products most associated with the DMs were Stingray, Capri, Corvette, Thunderbird, Celica, and hot rod.

Memory Map

The nodes on the memory map (see Figure 1) represent constructs from our interviews, and the connections between the nodes show associations. Only constructs mentioned by at least two-thirds of the participants from each generation appear on the map. We constructed the map primarily from the depth interview data, but examples also

FIGURE 1
Memory Map



came from the surveys. As such, the map represents a majority of our participants.

The most obvious distinction, or tension, in the map appears in the disconnect between "family car," represented on the left-hand side, and "sports car," represented on the right-hand side (i.e., the EM data primarily related to the family car and the DM data primarily related to the sports car). This tension of needing a safe vehicle while desiring a fun, sporty car existed for all generations, which is consistent with Solomon's (1983) proposition that an automobile can be used to identify with the individual sense of self or the family sense of self. Brown, Kozinets, and Sherry (2003) call such contradictions "paradessence," in reference to the paradoxical essence of a brand.

Levi-Strauss (1977) takes a structuralist approach to myth and proposes that the purpose of a myth is to provide a logical model that is capable of overcoming a contradiction. His argument is that (1) all cultures try to account for apparent contradictions in the world around them and (2) in almost all languages, myths follow similar structural lines in dramatizing these contradictions into story form to resolve them. In our interpretation of the data, we do not take such a strong structuralist perspective, but it is noteworthy that the memory map represents contradictions that consumers experience (e.g., the tension between other and self, the tension between family car and status car). This finding maps onto Holt and Thompson's (2004) man-of-action hero myth, which is a resolution of two opposites: the rebel cool (sports car) and the secure-but-boring breadwinner (family car).

Brands that can resolve the contradictions are successful. The brand's myth is the consumer belief that the brand offers a way to resolve a problem or situation that previously represented some kind of contradiction (Holt 2003). In the case of the successful PT Cruiser, the car resolved the contradiction by being both big and roomy (aspects of the family car), thus having some emotional comfort, and stylish, distinctive, and attention getting (which is associated with the sports car side of the map). As Rapaille (2004) said:

> What people told us is that "we're tired of these cars that have no identity. I have good quality, good gas mileage, good everything else, but when I see the car from a distance, I have to wait till the car gets close to know what it is, and I have to read the name." When you go to see your mother, she doesn't need to read your name to know who you are, you see? We want this reptilian connection. And so this notion of identity, absolutely key, was very reptilian for a car. Chrysler's other research told them people don't want to buy cars anymore, they want SUVs [sport-utility vehicles], minivans, etc.

From this perspective, brands with strong contradictions are viewed as "better." In other words, strong opposition leads to strong myth. By extension, brand positioning is superior if it can capture (and resolve) contradiction in its brand story. Companies with dying (or injured) brands are often companies whose brand myths have fallen behind or are out of tune with contemporary culture (Holt 2003). The problem with myth identification is that brands are complex, and people are even more complex. In many instances, there might be more than one myth that describes the product or brand. According to Levi-Strauss (1977), the binary opposition is mediated by a third term, which typically constitutes something valued in the culture. Consumer memory stories are situated in a broader cultural system of meanings. Cultural myths that manifest in consumer meanings are grounded in the collective cultural memory (Thompson 1997). Our data suggest that though all generations share a binary opposition or struggle, the third variable—how it is mediated or resolved—differs among the generations. Others have found gender differences in automobile ownership (Belk 2004), but the most overwhelming difference in our data was generational.

The Generation Xers

In our sample, the fear in post–September 11 America was still operating, though at an implicit level (i.e., no one acknowledged it directly). In this post–September 11 world, the Generation Xers were beginning to start families. The natural urge to relive or re-create their own childhood (as discussed in other texts; Levy 1981) is heightened by the reality that their own childhood was not really that good. They grew up in the era during which divorce was rampant, their self-centered baby boom parents often ignored them, women were breaking away from families to start careers, and so forth. Despite this difficult childhood environment, in our sample, the Generation Xers indicated in their video interviews that their EMs were something they cherished. This group also showed the strongest relationship between their EM and current car choice.

To make sense of this contradiction, members of this group created their own myths about their childhood. In almost all the EMs, the father was central to the experience. He was frequently a larger-than-life figure. Zoe remembered putting her own hand in her father's hand and noticing how it dwarfed hers; she remembered looking up at his seven-foot-tall figure and being amazed at how large he was; she recalled stopping during their childhood vacation, getting out of the car, and playing in a running creek with her siblings and her father reaching down and lifting them out. Later, she noted that she may have remembered this experience because of the fantasy of wanting to have a father who was involved in her life (that was the last trip they took together as a family; he separated himself from their lives after that point). Her current car was a red Jeep Cherokee; she said that she was drawn to it for its box shape and wondered now if she was influenced by the red station wagon of her childhood experience (it was also square shaped).

Zack recalled his EM as being in the back of the station wagon in the third seat (facing backward) as his father drove toward the vacation destination. About a half hour into the trip, he vividly recalled the car coming to a halting stop. Because he was facing the other direction, he did not see that his father had slammed on the brakes to miss hitting a deer in the road. He barely caught a glimpse of the deer before it ran off into the safety of the woods. He recalled a feeling of safety in the car when his father drove, as if any potential obstacle could and would be averted. That he was facing backward has additional symbolism in this memory. Later, he said that he enjoyed the feeling of isolation in the third seat; facing backward made him feel separate from his female siblings:

> I was in the third seat, sort of in my own world. Brought my toys back there. It was fun.... Sometimes I'd feel kind of isolated... It was great because I didn't have to worry about my sisters bothering me or my parents yelling at me.... It was kind of cool.

As Holt and Thompson (2004) note, the hero myth drives male behavior; we found that this was particularly the case with men, cars, and their current family. Stuart recounts the following experience:

> The first time I really noticed or cared about a car is when I got to go with my Dad to test drive a Trans Am. My family had just seen *Smoky and the Bandit*, and that is the car the hero of the movie, Burt Reynolds, drove to get away from all the bad guys. It was the car to have, and I was really excited.

Later, he said that as a child, he played with the Trans Am toy car in his backyard. He admitted that he had had a sports car at one time, but now that he was married with a child, he had an SUV. The interviews were conducted before the release of the Hummer and some of the larger SUVs, so at that time, such a car choice represented protecting and isolating oneself (or family) from the "bad guys" (drivers, terrorists) because it rode higher than other cars on the road. Lauer (2005) claims that consumers usually attribute buying SUVs to their safety and space, but he finds that safety is viewed as emotional rather than physical and that space is not interior cargo but rather social space—the privileged ability to traverse inhospitable terrain to remove oneself from society.

Another memory from Samantha evokes the dark side of the hero archetype (the destroyer). She recalled being driven by her father in his "souped-up" Toyota truck to school so she could be admired by the other kids because the truck was so cool. She and her brother were known as the "cool kids" because of the truck and would purposefully be late to school so that they could be driven in that chariot. Her EM was of her father crashing and destroying the car. That memory symbolized fear of having something taken away and of not having a strong hero to save the day.

A brand story that might be effective for reaching this generation would be one that evokes the mythic father figure. Such a story might show the current father as a hero, protecting his family from the bad guys and confronting and overcoming evil. The father would be viewed as being empowered and in control (some of the feelings that were taken away from him on September 11 in particular but also as he started a family and no longer had his freedom and his sports car).

The Baby Boomers

During the time of the interviews, the baby boomers were becoming empty nesters, and the responsibility of raising a family was not at the forefront of their experience. They were most influenced by the DMs they indicated in their video interviews and said that they were more pleasant and more cherished than any of the other generations. As Sally noted, "I'm at a point in my life where I can focus back on me, and when I look for a car today I am looking not for the practical hauling of kids but for the cute, sportiness that represents freedom from all those responsibilities." There was also a stronger relationship between the DM and the current choice behavior. Many respondents in our sample were considering buying a sports car (five men and one woman indicated that they were eyeing the Ford Thunderbird). This is consistent with Belk's (2004) finding that people in their middle age try to reclaim lost youth and all the excitement they associate with their late teenage years by buying cars that are reminiscent of those they desired when they were younger. As children, the baby boomers were the most spoiled by their parents. The angst that is evident in the Generation Xers and the interest in re-creating their childhood (in more positive ways) were not at all apparent in this generation. What appeared to be more prevalent was re-creating the need to break from parental control, and the memories featured either that break or putting off responsibility. Many of the memories featured convertibles along with feelings of freedom at "letting one's hair down."

Mike's first memory involved his uncle winning a Cadillac Eldorado convertible in a raffle. According to him, the car cost more than the row house in which his uncle lived in Little Italy. He remembered being impressed with the car and wishing he had one in his own garage today (though the car was way out of his price range). He remarked, "[G]oing through this exercise, a lot of my memories revolved around convertibles." When asked why, he said that they are carefree, not a responsibility car, and "yeah, [I] would like to buy one to relive my youth." He was one of the men eyeing the Ford Thunderbird.

Jim, who was also eyeing the Thunderbird, recalled his memory of being with his uncle in his 1955 Oldsmobile, "the most beautiful car I've ever seen,... red and white two-tone with lots of chrome." The memory involved a time when they drove through farmland at more than 100 miles per hour to get to his aunt's house. He said that "the experience taught me I like fast cars." He later bought two Oldsmobiles. His interest in the Thunderbird was that it "matched" his DM of his neighbor's canary-colored Thunderbird convertible. He remembered admiring it and enjoying being taken to school in it (as opposed to his parent's more confining sedan). He admitted being drawn to cars that are a little different, that people stop and notice.

Pat recounted her memory of being six years old and sitting in the backseat with her little brother in a car seat; her mom stopped at a neighbor's house and left them alone for a few minutes. She was always fascinated with driving and took that as an opportunity to practice, sitting behind the big wheel and moving the gears. What she did not realize was that she released the parking brake, and the car rolled down the driveway and across the street and hit (and left a large hole in) the house across the street. She recalls that "everyone was moving so slow, and so fast, at the same time." The most symbolic aspect of that experience was that she let her mom believe that she had not left the parking brake on, keeping that secret to herself for more than ten years and not taking responsibility for the accident.

Feelings of freedom, wanting to relive youth, and not taking responsibility are all associated with the Peter Pan image (or what Jung would call the "eternal boy/girl archetype"). The baby boomers' response to the fear of post–September 11 was to escape to their more idealistic adolescence. Therefore, brands that embrace remaining eternally young in body, mind, and spirit, as well as those that feature images associated with baby boomers' DMs, would appeal to this generation.

Silent Generation

The silent generation was perhaps the most intriguing. As children, they were war casualties in the sense that they were often overlooked, and their parents, who were faced with the Depression, worked long hours, and there was not much time for nurturing. Their life paralleled the development of the automobile, from the mass-produced Ford A, to the Corvair, to the 1957 Chevy, to the present. Their life has also been an internal struggle between the practicality to which their parents ascribed and the abundance available to them after World War II; for this generation, the struggle was not between family and sports car (on the memory map) but rather between practical and status car. Their life paralleled the growth, sophistication, and transformation of the automobile, and some aspired throughout their lifetimes to own the best car available. Others condemned that type of conspicuous consumption and the extravagance of the automobile as a status symbol, harkening back to their parents' more practical views about the role of cars. The view that eventually prevailed was revealed in their childhood memories.

For Alan, this struggle was ongoing. He grew up in a tenement building in Brooklyn. One of his EMs is of escaping the day-to-day squalor and misery by taking a ride in his uncle's Model A and being exhilarated when riding in its rumble seat. A wealthier neighbor owned a Buick, which he said represented "power ... [and] prestige," and he befriended the neighbor's "dippy" son so that he could ride in it on occasion. When he was older and had some money to buy a car for his business, he said,

> I guess I thought, why not indulge myself. I never do. I didn't even compare prices. I didn't shop. I just wanted to get this thing. It wasn't the car that I loved. I wanted to get a Buick. I never until now associated that Buick with [his neighbor's] Buick, but now I wonder. All those years, this thing was buried in my mind or burned in my heart.

He bought the Buick, and for him, it became a metaphor for his own personality. "Buick was right for me, quiet prestige, not showing like a Cadillac." This view of a Buick was consistent with what Social Research Inc.'s original 1954 study found about Cadillacs and Buicks; namely, Buicks were socially a notch below Cadillac, but for those on the way up, Buicks were considered reliable, sturdy cars for substantial people, whereas Cadillacs were resented as snobbish or snooty (Easton 2001). Currently, the more practical side of Alan won; he owned a minivan. He said, "there goes practical Alan again." Thus, although he was able to give into his desire for status at one time in his life, the practicality learned during his childhood years took over again.

Dennis wanted the status of owning something "new" and different. His EM was of his father bringing home a new car for the first time. "What an experience," he recalled, "the excitement of having a new car." He said that just having a new car was something special back then. He remembered climbing in and exploring it, the smell, and the awe of the experience in general. His DM was also about a new car. He said that "everyone is into something; my thing just happens to be new cars." He recalled many family photos taken in front of the car (rather than in the house or in front of the house). He said that his family did not know anyone who owned stocks or bonds, and everyone lived in roughly the same type of house; it was the car that differentiated people. His EM involved the Hudson Terraplane, which he thought looked a lot like the PT Cruiser ("a cute car.... Yeah, I'd buy one"). Again, his earliest experience infiltrated current preference.

Bob was a more practical son of the Depression. His EM involved taking the family car to visit his cousin, getting stuck in the muddy road, needing to band together to push the car, and pushing the car over his cousin's legs (who did not get hurt). He said that this was a fond memory and became a family myth; they would all laugh about it each time they visited. His memory symbolizes making the best out of a bad situation. With respect to cars, he said that his dad bought older cars until they dropped and then bought another older car. To his father, a car was a tool, not a toy: "Looking at new cars was not anything of interest to us because it would be like wanting to be the King of England. We knew we'd never be a king, and we knew we'd never have a new car." Bob's practicality in terms of cars continues. He currently owns a Dodge van. Previously, he owned a Mazda van, which he bought for $12,000. After approximately three years, he tried to turn it in and buy a new model but gawked at the $24,000 price tag, which he claimed was too high for basically the same van. He said that some of his friends were into buying showy cars, such as a Mercedes, and thinking that buying such cars would change them somehow, but he never saw the point (even though he could afford it).

The archetype relevant to members of this generation is the Midas/miser, the pull between being showy and buying the best while being practical and remembering their roots. For a brand that wants to engage the psyche of this generation, perhaps Alan said it best in his reference to the Buick: "quiet prestige."

A General Note on Archetypes and Deep Metaphors

Although the three generations could be best described through the archetypal stories we recounted, there was some overlap. For example, one male Generation Xer, who was the only one to feature his mother, recalled an experience in the car with her in which he played a game of sticking his hand out the window and holding it there as his mother accelerated. This sort of playful EM (and his other memories as well) would fit better with the Peter Pan archetype. This person did not have a family at the time of the interview, and thus some of these concerns were not pivotal to his life. His current car was a sports car (Trans Am), and he said that he chose it for the feelings of freedom and escape. Likewise, there was a female baby boomer whose EM was of her father driving her family's station wagon down a dark, windy road after a family visit to Santa's Village. Her father hit another car on the way home (everyone was fine). For this woman, safety has continued to be a foremost concern in her car choices, and she would probably respond well to the "father-as-hero" archetype described for the Generation Xers.

Marketing Implications

The memory data can be used to provide insights for marketers. For example, the objective memory data information described in the EM and DM sections could help mangers construct effective autobiographical ad campaigns or corporate communications (e.g., Baumgartner, Sujan, and Bettman 1992). The "generic events" represent the easiest entrée to the past (Barsalou 1988). The images, life themes, and landmark events (which we did not fully discuss in this article) could provide specific symbols and images to incorporate into consumer communications. By associating themselves with important childhood memory experiences, brands can benefit through the emotions brought forth as consumers relive those memories (in the manner of Proust and his "petite madeleine"). Within the EM and the DM experiences are similarities and differences that define the generations and suggest segmented communication strategies. In terms of similarity, the generic experiences and life themes were shared across generations. Consistent with Levy's ([1957] 1999) finding, some aspects of human nature and life remain unchanged. Consumers yearn for stable families, bettering their children's lives, and finding happiness. The differences are observed in the symbolic meaning attached to these memories (we discuss this in greater detail subsequently) and the landmark events associated with them, which would allow for more targeting of the collective memories of the different generations (Halbwachs [1950] 1980).

There was a mythic quality to the EM experiences that enabled us to analyze them not just for the literal information but also for their symbolism. Participants remembered themselves and the brands in terms of how they would like themselves to be (rather than how they actually were). As Vailliant (1977, p. 197) said, "It is all too common for caterpillars to become butterflies and then maintain that in their youth they had been little butterflies. Maturation makes liars of us all." The "lies" people tell about their childhood make them perfect for interpretation. Although some truth was probably associated with the memory stories, there are also many elements associated with present-day experiences (e.g., lifestyles; preferences; and current concerns, such as a preoccupation with post–September 11 America). In this way, people's idealized selves are projected onto the past.

According to Brown, Kozinets, and Sherry (2003), such a utopian ideal has only been hinted at by scholars, and it plays an important role in understanding brand meanings and connections. For brand managers who want to create an "authentic" self or image, connecting to consumers' past experiences provides a promising opportunity. As Belk (1990, p. 670) states, "Even though our nostalgia memories are essentially un-real and imaginary rather than objective and inherent in the objects that inspire them, we nevertheless insist upon the authenticity of these objects." Authenticity is an important aspect of brand identity (Keller 1993). Kelly (1998) claims that brand essence is the brand's DNA, or what it stands for to consumers. In our research, the meanings of the brand/product changed but continued to influence current preferences. Through one strategy, a brand could work to reconcile the overall tension in the map between focusing on the self and focusing on the family, or the sports car versus the family car, as the successful PT Cruiser has done. Note that since the time these interviews were conducted, the Crossfire, Escalade, and Hummer have all attempted to establish their own brand myths based on this conflict. An alternative strategy involves focusing on a particular generation or consumer type and then creating a brand myth toward these experiences, using the hero, Peter Pan, or the Midas/miser archetypes as guides.

General Discussion

The purpose of this article was to introduce EMs and DMs as projective techniques that marketers could use to uncover brand meaning. Our method was guided by researchers in psychoanalytic counseling and social psychology, as well as the well-established G. Clotaire Rapaille. The consumer memory stories were analyzed both quantitatively and qualitatively. In the following sections, we discuss our results in terms of positioning a brand across the consumers' life cycle, how our findings are related and could be used to add a narrative dimension to the conception of the brand schema, and the strengths/weaknesses of this memory elicitation method compared with other projective methods.

Life Cycle

Products can serve different purposes throughout a person's lifetime. Numerous brands, each exuding different personality traits, correspond to these varying needs. This finding is congruent with contemporary personality research, suggesting a situational component best revealed through narratives. A major implication is that automobile manufacturers should be aware of the role that vehicles have played in consumers' past to understand what they want in the future. This insight is especially important in industries in which design planning occurs far in advance of product introduction.

The consumer–brand relationship is dynamic and changing, but it is also cyclical. Certain key experiences can provide insights into what the consumer will desire in the future. We found that EMs of car experiences were indicative of choice in a family vehicle later in life. For example, defining experiences provided insight into the selection of a sports car, after family issues had been handled. In addition, EMs of safety and functioning become an issue (e.g., from discussions with the silent generation participants). For example, children today who are escorted to and from school or who go on family vacations with their Generation Xer parents in their family's Hummer will seek similar design attributes and present-day associations when they buy their own family car 30 years from now; they will seek their own form of emotional safety.

A traditional way of thinking is that the brand exists as an entity and possesses its own set of attributes and "personality traits." One limitation of this approach is that it might be difficult for managers to find a way to make these traits meaningful to the consumer. The narrative approach of examining the brand is based on the assumption that a brand takes on its meaning to consumers through their interactions with the brand (or product). For example, the trait way of viewing a Buick might be to ascribe certain adjectives to the brand, such as "old," "dull," or "stodgy." In contrast, the narrative way of viewing the brand would be to associate a Buick with people's experiences of riding in the back of their grandparents' car, of sucking on butterscotch candy, of being taken to the movie theatre, and so forth.

Although marketing scholars have recognized the importance of the experiential nature of the brand, this has not been fully integrated into how brand management models are defined (cf. Brown, Kozinets, and Sherry 2003). In the past, a brand's schema has been defined as all the associations connected to the brand in memory (Keller 1993), which are assumed to be stored in a semantic-type network. This research offers another perspective that is consistent with the literature on the relational aspect of brands (e.g., Fournier 1998). In this approach, brands and their associated meanings emerge from the interactions they have in consumers' lives. Key to understanding what a brand means today is unlocking what consumers remember about their usage of the brand or product in the past. From this perspective, marketers are "meaning managers," and consumers are cocreators of brand essence (Brown, Kozinets, and Sherry 2003; Brown and Sherry 2003).

Methodological Considerations

There has been a resurgence of interest in identifying research methods that "dig deeper" into the consumers' unconscious (e.g., ZMET, physiological measures, response-latency techniques). Nonetheless, some projective techniques have been around for a long time (e.g., TAT, Q-sort, Rorschach). The childhood memory elicitation method is best classified as a projective technique based on consumer storytelling, and the memory elicitation procedure we described here identifies important memory markers as the makings of consumer memory stories. Note that this approach is different from traditional storytelling research (i.e., Levy 1981), which asks in general about family tales or stories; from life-story interviews, which probe the entire life history and can last three to five hours; from the TAT, which develops pictures or cartoons that "ask questions" to spur participant storytelling (Rook 1988); and from the ZMET, in which participants' own images direct the storytelling.

The memory elicitation method begins at the individual level; people recount their EMs and DMs of a product. Their recollection process is enhanced by allowing a time lag between the initial contact and the main session, during which their "synapses" begin "warming up" childhood associations. The memory walk further encourages them to recall earlier points in their lives, and the short interview session helps them form a comprehensive narrative. As other researchers using a memory method have noted (Lupton 1994), these important memories may rest at a more unconscious level and be difficult to articulate without such assistance. Indeed, in our Coca-Cola pilot work, we found that the memories elicited in a focus group session were different from those recalled as a result of the memory elicitation procedure. We also found that when focus group participants read memory stories elicited by others during a memory elicitation session, they related to them much more than the stories discussed by the group itself. This finding is consonant with Halbwachs's ([1950] 1980) observation that though remembering may appear to be an individual process, no "individual" memory exists, and the social and cultural influences result in many similarities (see also Lupton 1994).

Although other researchers have focused on frameworks for deriving insights from consumer stories (e.g., Thompson 1997), the current research focuses on a technique to uncover important stories, or the "content" of what researchers analyze. The main advantage of this method over existing methods is that consumers' EMs and DMs provide a quick, symbolic snapshot of the consumer, offering insight into how present concerns, past experiences, and lifestyles converge in the creation of a memory story. Researchers have found high test–retest reliability in thematic aspects of EM and DM techniques (some researchers found 80% test–retest reliability for matching specific events, and this is probably higher for generic memories or repisodic events; see Bruhn 1985).

The output of the method, as we discussed previously, offers managers a concrete means to market and promote their brands. For example, the generic memory experiences can be used to guide a memory-referencing ad campaign, and the emergent myths can be used to help brands develop their own brand story. With any research technique, the benefits of having a larger, more generalizable sample must be weighed against the desire for a deep understanding of consumers. The memory elicitation method strikes a good balance by running the age cohorts in groups of 20 with multiple video cameras. In this way, participants have an opportunity to tell their memory stories while they are still fresh from the elicitation session. Because participants might feel self-conscious during the relaxation and memory walk, the group setting reduces this feeling while maintaining the individual integrity of the memory recollections. Because our focus is on EMs and DMs (and the role they played in participants' lives), the resulting narratives are shorter and more focused than might be expected from a depth or typical-life-story interview, which makes analysis more efficient. We followed the memory elicitation with longer interviews and note that that data were critical in forming the overall memory map. However, Rapaille uses only the data from the memory session in his interpretation, and we found that the videotaped memory stories provide the most useful data for interpreting the symbolic and mythic qualities associated with these memories.

The psychotherapist Franz Plewa (1935) finds that EMs offer more insights into dynamics of an individual than any other psychic expression. Participants report "having fun" on their memory journey and "learning something about themselves," and it builds a nonthreatening, empathetic relationship. We found that this was the case especially with the silent generation, who genuinely enjoyed the reminiscing process. We also found that Generation Xers felt positive about their experience: "I would like to begin by saying that I was very surprised how many memories came back to me as you were leading us back in time; it was a cool activity."

Further Research

The use of childhood memories to understand current consumer preferences may increase as research derived from psychoanalysis and social psychology develops. We hope that the current controversies regarding Rapaille will not diminish that effect; note that Holbrook (1988) ascribed Ernest Dichter's flamboyant personality and outrageous claims as one of the reasons for the demise of projective techniques in marketing. There will need to be more studies to establish validity and reliability of our approach. However, its usefulness to marketing researchers will depend on more academic studies exploring childhood memories in the consumer domain. For example, although singular EMs have been an important aspect in the clinical domain, in which individual insight is sought, they may or may not be as important in the consumer domain, in which myths or repeated incidents might be more salient or relevant. It is also important to understand the best methods for eliciting memories that are both useful and expedient for marketing managers. Finally, it is important to develop comprehensive perspectives for analyzing these memory meanings.

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S. Sriram, Subramanian Balachander, & Manohar U. Kalwani

Monitoring the Dynamics of Brand Equity Using Store-Level Data

Management of brand equity has come to be viewed as critical to a brand's optimal long-term performance. The authors evaluate the usefulness of brand equity estimates obtained from store-level data for monitoring the health of a brand. They use a random coefficients logit demand model calibrated on store-level scanner data to track brand equity estimates over time in two consumer packaged goods categories that experienced several new product introductions during the period of the empirical investigation. Using these tracked measures, the authors also study the impact of marketing actions, such as advertising, sales promotions, and product innovations, on brand equity. They find that the brand equity estimates effectively capture the high equity of strongly positioned popular brands and brands that command a significant price premium in niche markets. Using an example, the authors illustrate how these brand equity estimates can be used to monitor changes in brand equity, which measures such as market share may fail to capture. The substantive results indicate that advertising has a positive effect on brand equity in both the product categories, whereas the effect of sales promotions is not significant in either category. Furthermore, the results reveal that new product innovations have a positive impact on brand equity and can explain a significant proportion of its variation. Overall, the analysis shows that a brand manager can track brand equity using store-level data, gain insights into the drivers of the brand's equity, and manage these drivers to achieve brand equity targets.

In contemporary marketing, brand equity has emerged as a key strategic asset that needs to be monitored and nurtured for maximum long-term performance. A widely used definition of brand equity characterizes it as the value added by the brand name to a product (Farquhar 1989). Higher brand equity can help a brand become more profitable through higher brand loyalty, premium pricing, lower price elasticity, lower advertising-to-sales ratios, and trade leverage (Keller 1998). Given the advantages that accrue to a brand with high equity, effective brand management requires careful monitoring of its equity over the long run. Recently, many firms have appointed brand equity managers who are responsible for monitoring brand equity to both detect signals of erosion in a brand's equity and approve programs to enhance it (Aaker 1991).

Many commercially available methods for tracking brand equity, such as EquiTrend and Brand Asset Evaluator, employ consumer or expert surveys to measure brand equity (Aaker 1996). In the marketing literature, Park and Srinivasan (1994) offer such a survey-based measure of brand equity. Keller (1993) proposes a conceptual framework for measuring brand equity using customer surveys. Although survey-based measures can be useful for tracking brand equity and can provide useful diagnostic input to managers, Park and Srinivasan note (p. 286) that a limitation of their method is that "it depends on the ability of consumers to accurately report their relative brand preferences." Conversely, the availability of store-level scanner data offers an alternative way to measure and track brand equity that is free of self-report errors. Brand equity estimates based on store-level data in combination with traditional survey-based measures can add to a manager's confidence in formulating marketing programs designed to maintain and build a brand's equity. Because marketing practitioners in consumer packaged goods categories often use store-level data to monitor brand performance by store type and geographical region and to assess the impact on sales of changes in advertising, price, and distribution (Bucklin and Gupta 1999; Shoemaker and Pringle 1980), such data with appropriate adjustments can also be used to generate brand equity estimates for tracking purposes. Using store-level data, as opposed to household-level data, to track brand equity has two advantages: First, store-level data are considered less vulnerable to sample selection bias than survey or individual-level scanner-panel data (Bucklin and Gupta 1999). Second, because store-level data can be obtained across several retailers in various geographic regions, managers can use these data to track the health of their brands across geographic regions and with respect to various store brands.

In this article, we evaluate the usefulness of brand equity estimates obtained from store-level data for tracking

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the health of a brand. Kamakura and Russell (1993) propose that the intercept of a consumer's utility for a brand, as estimated from individual choice data, can measure a brand's equity (see also Srinivasan 1979). The idea is that the brand intercept identifies the component of utility that is not explained by tangible attributes and other marketing variables. Although such a brand intercept can be similarly estimated from store-level data for tracking purposes, there are several critical outstanding issues with respect to the reliability and validity of this measure for tracking brand equity. Thus, a manager presented with the intercept measure for tracking brand equity may have the following concerns: (1) Is the intercept measure reliable enough to be used to monitor brand equity? (2) Is the measure sensitive enough to capture changes in brand equity induced by marketing-mix changes and competitive activity? (3) Does the measure respond in expected ways to marketing-mix elements, such as advertising, sales promotions, and product innovations? and (4) Will estimation with store-level data affect the properties of the measure with respect to these issues? In this article, we address these important issues pertaining to the suitability of the intercept measure to track brand equity.

An overview of our empirical approach is as follows: Using store-level data from two consumer packaged goods categories—namely, toothpaste and dish detergents—we carry out our analysis in two stages to realize our research objectives. In Stage 1, we use weekly sales data to obtain quarterly estimates of the brand intercepts in a product category over a period of up to 30 quarters. Our estimation of brand intercepts in the Stage 1 analysis uses recent methodological advances (Berry, Levinsohn, and Pakes 1995) to estimate demand models from aggregate data. We then evaluate these intercept estimates for their suitability to measure and track brand equity. In our Stage 2 model, we relate the estimated quarterly brand equities to data on quarterly advertising, sales promotions, and product innovations undertaken by the brands. A comparison of this estimated relationship with that which theory predicts can help us validate the intercept estimates as measures of brand equity. Furthermore, the Stage 2 analysis enables us to infer both the short-term and the long-term effects of advertising, sales promotions, and product innovations on brand equity.[1] We can then use these effects to obtain managerial insights into the profitability of alternative strategies for building brand equity. The ability to relate marketing actions to brand equity and the latter, in turn, to profitability is becoming increasingly important with the growing management focus on marketing productivity (see, e.g., Rust, Lemon, and Zeithaml 2004; Rust, Zeithaml, and Lemon 2000; Srinivasan, Park, and Chang 2005). Using a survey-based approach, Srinivasan, Park, and Chang (2005) relate marketing actions to brand equity and resultant profitability. Rust, Lemon, and Zeithaml (2004) also use a survey-based approach and consider the effect of a broader set of drivers on profitability through their effect on individual-level customer equity. Unlike these studies, however, our approach uses store-level data that are readily accessible to brand managers, but such data also limit the number of drivers and types of marketing expenditures that can be analyzed in comparison with the other survey-based approaches.

The substantive conclusions from our empirical analysis are as follows: Using a reliability check across two split-store samples and correlations with other brand equity measures, we infer that the Stage 1 brand intercept estimates may be suitable for tracking brand equity. The brand intercept estimates correlate well with other measures of brand equity and appear not to be driven by the size of the brand alone, as indicated by market share or revenues. Indeed, we find that the brand intercept estimates effectively capture the high equity of strongly positioned popular brands and brands that command a significant price premium in niche markets. From a diagnostic point of view, using an example, we illustrate how managers can use these brand equity estimates to monitor changes in brand equity, which measures such as market share may fail to capture. This analysis and our Stage 2 model results suggest that the brand equity estimates are indeed sensitive to marketing-mix changes and competitive activity, as they should be.

This article contributes to the brand equity literature in the following ways: First, to our knowledge, this is the first study to address the important issues we identified pertaining to the suitability of the brand intercept measure estimated from store-level data to track brand equity. As we discussed previously, when tracking considerations are important, the dynamic behavior of the intercept measure and evidence of its validity as a measure of brand equity over time become important concerns. These concerns are not addressed in the work of Kamakura and Russell (1993), because they capture only a snapshot of brand equity in time. Conversely, Jedidi, Mela, and Gupta (1999) capture the temporal changes in brand equity due only to the marketing-mix variables of advertising and promotion. Because other factors, such as product innovation and competitive activity, can affect brand equity, their analysis does not capture all the time-varying changes in brand equity.[2] Thus, their approach cannot be used to track brand equity. Second, from a methodological perspective, we provide a framework for implementing a brand equity tracking approach using store-level data, though the individual methodological pieces that go into this framework have mostly been developed previously. Using this framework, we show that a manager can not only track brand equity using store-level data but also gain insights into the drivers of brand equity and into how these drivers could be managed to achieve brand equity targets. Finally, we obtain substantive results about inertia in brand equity and about the drivers of brand equity. Although other researchers (e.g., Ailawadi, Lehmann, and Neslin 2003; Jedidi, Mela, and

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[1] We use a two-stage approach because though consumer choice varies from week to week because of changes in the marketing mix and the store environment, there may not be measurable changes in brand equity on a weekly basis. Although our Stage 1 model uses weekly sales data to infer average brand equity on a quarterly basis, our Stage 2 model tries to explain the dynamics of the quarterly brand equities.

[2] Indeed, shocks to brand equity due to such changes are not separately identified in Jedidi, Mela, and Gupta's (1999) model from the shocks to sales.

Gupta 1999) have obtained similar substantive results on advertising and promotion, we are the first to study the influence of product innovation on brand equity.[3]

We organize the rest of this article as follows: We begin with a review of the relevant literature on consumer and firm-based measures of brand equity and the expected effects of marketing actions on brand equity. Then, we present the Stage 1 model used to estimate brand equity on a quarterly basis. Next, we present the Stage 2 model used to estimate the effect of marketing actions on brand equity. Then, we describe the data and the operationalization of the variables. Next, we present our empirical results in the toothpaste and dish detergent markets. Then, we discuss the managerial implications of our model. Finally, we provide some concluding comments.

Literature Review

Brand Equity: Consumer and Firm Perspectives

Brand equity has been defined as the added value endowed by the brand name to a product (Farquhar 1989). Although there is general agreement with this conceptual definition of brand equity, approaches to measuring brand equity have taken one of two perspectives. On the one hand, the firm-based perspective focuses on measuring the added value in terms of cash flows, revenues, market share, or similar measures. For example, Simon and Sullivan (1993) use financial market information to calculate incremental cash flows attributable to branded versus unbranded products as the brand equity measure, and Mahajan, Rao, and Srivastava (1994) use the purchase price when the brand is sold or acquired. Ailawadi, Lehmann, and Neslin (2003) use product-market data to calculate the difference between the revenue of a branded product and that of the store brand; they call this a "revenue premium" measure of brand equity. Firm-based measures, such as revenue premium, provide a single objective number that is credible to senior management and the financial community and acts as a useful guide to the value of a brand in mergers and acquisitions.

On the other hand, a consumer-based measure of brand equity is based on the value consumers derive from the brand name. Some researchers define this added value as the positive associations, awareness, loyalty, and perceived quality of the brand (Aaker 1991); as the differential effect of brand knowledge to the marketing of the firm (Keller 1993); or as the price premium that consumers are willing to pay for the brand (Park and Srinivasan 1994). Srinivasan (1979) and Park and Srinivasan (1994) isolate brand equity as the component of the overall preference not explained by objectively measured attributes. Kamakura and Russell (1993) estimate a measure of brand equity—they call it "brand value"—as the component of overall utility not explained by "situational factors," such as price and other short-term marketing-mix influences on choice. Consumer-based measures of brand equity can provide valuable insights and diagnostics for the marketing or brand manager concerned about a brand's value to consumers. Such measures can effectively capture the equity of strongly positioned popular brands and the equity of brands that enjoy high consumer loyalty and command a significant price premium in niche markets. Thus, firm- and consumer-based measures provide different but complementary perspectives on brand equity, and both are useful in managing brand equity.

Effect of Marketing Actions on Brand Equity

The marketing literature suggests that advertising can affect brand equity through favorable associations, perceived quality, and use experience (Keller 1998). In addition, advertising can act as a signal of product quality (Milgrom and Roberts 1986). Using a firm-based measure of brand equity derived from financial data, Simon and Sullivan (1993) find a positive relationship between advertising and brand equity. Using household purchase data, Jedidi, Mela, and Gupta (1999) also find a positive relationship between advertising and brand equity. Thus, we expect that advertising has a positive effect on brand equity.

Although sales promotions may boost a brand's sales in the short run, there is some discussion about their potential impact on brand equity. Keller (1998) suggests that the frequent use of price promotions can create or strengthen a "discount" association with the brand, thus diminishing its brand equity. Moreover, price promotions may train consumers to buy the brand only when it is available on a promotional deal. They may do so by lowering the reference price, which would reduce the premium that can be charged for the brand name (Blattberg, Briesch, and Fox 1995) and, thus, its equity. Some empirical studies (e.g., Jedidi, Mela, and Gupta 1999) find a negative relationship between brand equity and promotions in the long run. However, Aaker (1996) posits that though price promotions have the potential to damage a brand's equity by focusing on price, they can also support the brand. Learning theory suggests that the shaping of consumer behavior through promotions can lead to attitudinal loyalty (Rothschild and Gaidis 1981), thus enhancing brand equity. Thus, although a preponderance of studies suggests that promotions reduce brand equity, an alternative viewpoint is that well-executed promotions can strengthen it.

Another marketing variable that can have a significant impact on brand equity is product innovation. Product innovations, such as the inclusion of significant new features (e.g., fluoride in toothpaste for cavity prevention), can create differentiation, enhance a brand's value proposition, expand usage contexts, and block competitors (Aaker 1996). In addition, they can be used to revitalize the brand. Product innovations are especially critical for performance-based brands whose sources of brand equity rest primarily in product-related associations (Keller 1998). Correspondingly, failure to innovate can have dire consequences, and brands may need to innovate to maintain their relevance and, ultimately, their customer base. Keller (1998) cites the example of how Jiffy Pop popcorn, made to be cooked over a stove, became obsolete because of the widespread adoption of the microwave oven and because of its failure to innovate. Despite the importance of product innovations in building and maintaining brand equity, there has been little academic research on their effect on brand equity.

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[3] Unlike Jedidi, Mela, and Gupta (1999), we allow for endogeneity of advertising and sales promotions in estimating their effects on brand equity. We also estimate carryover effects of these variables on brand equity instead of assuming a value based on previous studies.

The Stage 1 Model: Brand Equity Estimation and Tracking

Model

In Stage 1 of our analysis, we use weekly store sales data to estimate brand equity values on a quarterly basis. We consider a market with utility-maximizing households, which in a given week t may choose to purchase a product variant j (j = 1, 2, ..., J_t) within a category or may purchase an outside good (equivalent to not purchasing in the category, denoted by j = 0). We consider each product variant a bundle of characteristics, one of which is a brand name denoted by k (k = 1, 2, ..., K). In general, the total number of product variants, J_t, is greater than K, because a brand's offerings may come in several sizes and formulations to yield several distinct product variants. Note that the number of product variants, J_t, can vary over time as new brands or new variants of existing brands are introduced and other variants are phased out. We represent the utility that household h shopping at store s derives from buying product variant j, j = 1, 2, ..., J_t, in week t occurring in quarter q as follows:

$$(1) \qquad U_{hjst} = \bar{\beta}_q + \beta_{0hkq} + \beta X_j + \alpha_h M_{jst} + \xi_{jst} + \varepsilon_{hjst},$$
$$j = 0, 1, 2, \ldots, J_t,$$

where $\bar{\beta}_q$ is the quarter-specific intercept term, β_{0hkq} is the coefficient representing the utility of the brand name k of alternative j during quarter q, X_j is a vector of other product attributes for alternative j (e.g., size, flavor) and for product variant j in store s in week t, M_{jst} is a vector of marketing-mix variables (e.g., price), ξ_{jst} is the mean utility to consumers due to unobserved variables, and ε_{hjst} represents the idiosyncratic preference of household h. The coefficient β is the vector of consumer taste parameters for product characteristics (except the brand name), and α_h represents the vector of response parameters to marketing-mix variables for household h. We assume that consumers in week t will choose to purchase one of the J_t product variants or settle for the outside good, depending on the utility they expect to derive from each alternative.

We allow for random effects in the brand intercepts and the response parameters to account for consumer heterogeneity. In our application, for parsimony, we allow for heterogeneity only in the brand intercepts and price sensitivity.[4] Specifically, we assume the following functional form for heterogeneity:

$$(2) \qquad \beta_{0hkq} = \beta_{0kq} + \sigma_k v_{hk}, \; k = 1, 2, \ldots, K,$$
$$\alpha_h = \alpha + \sigma_\alpha v_{h\alpha},$$

where β_{0kq} is the mean brand equity of brand k in quarter q, α is the vector of mean response parameters, σ_k and σ_α are the standard deviations of the parameters, and v_{hk} and $v_{h\alpha}$ are drawn from standard normal distributions. In line with prior studies in the literature (see, e.g., Jedidi, Mela, and Gupta 1999; Kamakura and Russell 1993), we use the brand intercepts, β_{0kq}, in Equation 2 as a measure of the brand's equity. Note that we estimate the brand equities on a quarterly basis. If we were to measure brand equity at the weekly level, it might be too sensitive to sales shocks that could be unrelated to brand equity, such as out-of-stocks. Thus, a moderately long period is likely to have the optimum level of sensitivity and stability. A quarter seems to be a natural choice given that it is a standard reporting and planning period for firms.

Similar to prior studies in the brand equity literature (see, e.g., Ailawadi, Lehmann, and Neslin 2003), we measure brand equity with respect to the store brand.[5] Because the store brand is the closest thing to a "no-name" brand in our data, measuring brand equity with reference to the store brand is consistent with the definition that it is the added value the brand name provides. Correspondingly, for identification, we set the coefficient β_{0kq} for the store brand equal to zero. Thus, β_{0kq} measures the incremental utility of brand k with respect to the store brand, and the intercept $\bar{\beta}_q$ captures the store brand's utility in quarter q with respect to the outside alternative.

We wish to point out that this intercept brand equity measure, β_{0kq}, can be readily transformed into a measure of market share premium that may accrue to a product variant offered by brand k relative to an identical variant offered by the store brand name. This transformed measure, $[\exp(\beta_{0kq})]$, which increases monotonically with β_{0kq}, is the market share that any product variant of brand k would command in quarter q as a multiple of the market share of an identical variant offered with an identical marketing mix by the store brand in that quarter.

For the sake of identification, we set the baseline utility of the outside good to zero, except for the effect of special events (e.g., a holiday) and store-level demographic variables. Thus, $U_{h0st} = \psi E_t + \varphi D_s + \varepsilon_{h0st}$, where E_t is an indicator variable for special events and D_s is a vector of demographic variables that corresponds to store s. The inclusion of special events, such as holidays, in the expression for U_{h0st} enables us to capture the effect of such events on the intrinsic value of the product category to consumers. The store-level demographic variables, D_s, enable us to capture heterogeneity across stores. Assuming that ε_{hjst} are distributed i.i.d. with a Type I extreme value density function and by integrating across all households, we obtain the aggregate market share ms_{jst} for week t in quarter q as follows:

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[4] Our robustness checks reveal that the key substantive results remain unaltered with the additional inclusion of attribute heterogeneity.

[5] An alternative approach would be to measure the brand equities with respect to the outside alternative. Such a measure is likely to be equally useful except in cases in which the store is losing sales in a particular category to competitors or other channels. In such a case, estimates of brand equities of all the brands are likely to be lower, even without any real change in the value of the brands. Measuring brand equity with respect to the store brand avoids this problem.

$$(3) \qquad ms_{jst} = \int \frac{\exp(\delta_{jst} + \mu_{hjst})}{1 + \sum_{j'=1}^{J} \exp(\delta_{j'st} + \mu_{hj'st})} f(\nu_h) d\nu_h,$$

where $\delta_{jst} = \bar{\beta}_q + \beta_{0kq} + \beta X_j + \alpha M_{jst} - \psi E_t - \varphi D_s + \xi_{jst}$, $\mu_{hjst} = \sigma_k \nu_{hk} + \sigma_\alpha \nu_{h\alpha} M_{jst}$, and $f(\nu_h)$ is the distribution of heterogeneity. The integral in Equation 3 is evaluated numerically (Nevo 2000).

Estimation

In Equation 1, the term ξ_{jst} captures the effects of variables unobservable to the econometrician but observed by the retailer and consumers. Examples include unobserved product characteristics, such as shelf location, shelf space, and other demand drivers at the store, that vary over time (Chintagunta 2002). Because retailers observe ξ_{jst}, they could incorporate this information in setting the price for period t. The resulting correlation of these endogenous variables with ξ_{jst} calls for the use of instrumental variables in the estimation. The model can be estimated by combining generalized method of moments with an "inversion" technique (Berry, Levinsohn, and Pakes 1995). For the details of the estimation, we refer interested readers to Nevo (2000).

The Stage 2 Model: Effect of Marketing Actions on Brand Equity

Model

In our Stage 2 model, we examine the effects of advertising, sales promotions, and product innovations on our quarterly brand equity estimates from the Stage 1 analysis. Our Stage 2 analysis helps us validate the brand equity measure and understand the relative impact of different marketing actions on brand equity. Because the effects of marketing actions on brand equity are likely to last beyond the current period, we use the following partial adjustment model (see Clarke 1976; Mela, Gupta, and Lehmann 1997) with brand-specific random effects to estimate the effects of advertising, promotions, and product innovation on brand equity:

$$(4) \quad \beta_{0kq} = \gamma_{0k} + \lambda\beta_{0kq-1} + \gamma_1 Ad_{kq} + \gamma_2 Pr_{kq} + \gamma_3 In_{kq} + \varepsilon_{kq},$$

$$\gamma_{0k} = \gamma_0 + \zeta_k,$$

where β_{0kq}, Ad_{kq}, Pr_{kq}, and In_{kq} are the mean brand equity, advertising, promotion, and product innovation, respectively, of brand k in quarter q and $\{\gamma_0, \lambda, \gamma_1, \gamma_2, \gamma_3\}$ is the set of parameters to be estimated. Furthermore, the term ζ_k captures the brand-specific random effect, and ε_{kq} is an error term. The parameter λ may be interpreted as the level of inertia in brand equity, and γ_1, γ_2, and γ_3 represent the contemporaneous effects of advertising, promotions, and product innovations, respectively, on brand equity. The random-effects specification of Equation 4 implies that the composite error term will be $\varepsilon_{kq} + \zeta_k$, and thus the error terms of each brand will be correlated (Greene 2000, p. 567). The long-term impact of advertising, sales promotions, and product innovations is given by $\gamma_i/(1 - \lambda)$, i = 1, 2, 3. We can obtain the standard errors of these long-term measures using the delta method (Greene 2000). Note that Equation 4 implies that the carryover coefficient for the three marketing-mix variables—advertising, sales promotions, and product innovations—is the same (Johnston 1984). Although such a model has the advantage of parsimony, we test whether advertising, sales promotions, and product innovations have the same lag structure (Johnston 1984).

Estimation

In estimating Equation 4, we address the following issues to obtain consistent parameter estimates: (1) endogeneity of advertising and sales promotions that results from managers choosing these variables in response to brand equity levels, (2) incorporating the Stage 1 standard errors that correspond to the dependent variable, and (3) incorporating the Stage 1 standard errors that correspond to the independent variables. In addition, we need to account for the correlation between the error terms of a particular brand due to the random-effects specification. We use an adjusted three-stage least squares (3SLS) approach to tackle all these issues. We discuss the details of our estimation procedure in Appendix A.

Data Description and Operationalization of Variables

Data Description

We use the Dominick's Finer Foods database made available by the University of Chicago. The data consist of weekly observations of sales, shelf prices by unique Universal Product Code (UPC), and daily store traffic for most of the stores operated by Dominick's Finer Foods in the Chicago area. We supplement these data with data on the monthly national advertising expenditures of brands, which we obtained from TNS Media Intelligence. We apply our framework for monitoring brand equity using the data from the toothpaste and dish detergent categories (excluding automatic dishwasher detergents). These categories are characterized by the presence of strong brands and also have substantial advertising and sales promotion expenditures. Moreover, they experienced the introduction of new brands and attribute formulations, which should lead to interesting dynamics in brand equity in these categories. The data span approximately 30 quarters from 1989 to 1997. We treat sales of a product variant in each store and week within a quarter as an observation for estimation of the Stage 1 model.

Toothpaste Category

Our analysis of the toothpaste category is based on 486 UPCs with six brands that account for 84% of UPCs and 97% of sales in the category. Descriptive statistics for the brands included in our analysis appear in Table 1, Panel A. The leading brands in terms of market share are Crest and Colgate, which have 35% and 27% shares, respectively. Notably, there is a high dispersion in prices across brands, and Mentadent and Arm & Hammer (A&H) sell at a significant price premium over other brands. Arm & Hammer,

TABLE 1
Descriptive Statistics

A: Toothpaste

Brand	Mean Quarterly Sales (oz.)	Mean Quarterly Revenue ($)	Mean Quarterly Price ($/oz.)	Mean Quarterly Share (%)	Average % of UPCs on Deal in a Quarter	Average Quarterly National Advertising (in Millions of Dollars)
A&H	132,511	67,527	.510	5.42	19.55	2.75
Aquafresh	239,402	87,335	.374	10.24	22.78	4.63
Close-Up	149,926	48,544	.338	5.97	27.60	.95
Colgate	662,733	227,723	.347	27.19	17.50	7.93
Crest	854,465	308,994	.362	35.47	19.02	13.02
Mentadent	123,473	91,244	.755	5.46	30.87	9.41

B: Dish Detergents

Brand	Mean Quarterly Sales (oz.)	Mean Quarterly Revenue ($)	Mean Quarterly Price ($/oz.)	Mean Quarterly Share (%)	Average % UPCs on Deal in a Quarter	Average Quarterly National Advertising (in Millions of Dollars)
Ajax	638,193	33,013	.054	4.74	20.80	.29
Dawn	3,369,961	202,546	.061	24.98	14.72	4.88
Ivory	1,487,602	89,382	.059	10.91	22.35	2.85
Joy	1,473,495	86,520	.057	10.89	10.28	1.42
Palmolive	2,850,432	170,741	.061	21.64	11.70	2.61
Sunlight	1,560,109	77,361	.053	12.13	15.36	.42

which entered the market with its baking soda formulation, was relatively new at the beginning of our observation window. The other major entrant in this market was Mentadent, which entered midway in our data with the baking soda and peroxide formulation.

Dish Detergent Category

Our analysis is based on 173 UPCs with six brands that account for 98% of UPCs and almost 100% of sales in the category. Descriptive statistics for the brands included in our analysis appear in Table 1, Panel B. The major brands in this category are Dawn and Palmolive, which have 25% and 22% market shares, respectively. Unlike the toothpaste category, we do not have any premium-priced brands that serve niche markets. Although no new brands entered the dish detergent market during the period of our analysis, product modifications based on two new attributes—antibacterial and "ultra" product formulations—were introduced. Procter & Gamble was the first to introduce ultra formulations of its brands—Dawn, Ivory, and Joy—in the third quarter of 1995, and this was quickly followed by Palmolive. The ultra formulations were superconcentrated versions of the regular dish detergent and came in bottles two-thirds the size of a standard bottle but typically sold for the same price as regular dish detergents. The rationale was that the ultra versions required the use of one-third less detergent to get the same results in terms of dishes washed. Notably, the ultra version product variants accounted for more than 60% of the category sales within six quarters after their introduction.

Operationalization of Variables

The Stage 1 model. First, we discuss the product characteristics. In the toothpaste category, we define product variants on the basis of five characteristics: brand name, gel (versus paste), baking soda, peroxide, and size. We chose gel, baking soda, and peroxide product attributes because of their importance as judged from business press articles and the relative market shares of the product variants incorporating these attributes, which were 22%, 17%, and 11%, respectively. Of these three attributes, baking soda was introduced just before the beginning of the period for which we have data, and peroxide was introduced in the middle of the period. We include dummy variables to capture the presence (or absence) of these attributes. In addition, we classify size into five different categories (extra small, small, medium, large, and extra large), which results in four dummy variables. We then aggregate sales over all the UPCs that possess the same characteristics to yield sales of the product variants. This aggregation gives us 76 variants and an average of 40 variants each quarter.

In the dish detergent category, we define product variants on the basis of five characteristics: brand, lemon scent, antibacterial formulation, ultra formulation, and size. Again, we chose the product attributes of lemon scent, antibacterial formulation, and ultra formulation because of their importance as judged from business press articles and the relative market shares of the product variants incorporating these attributes, which were 13%, 7%, and 50%, respectively. We use dummy variables to capture the presence or absence of these attributes. As in the toothpaste category, two of these attributes, antibacterial and ultra formulations, were introduced during the period for which we have data. We use four dummy variables to capture five different size classifications. To account for the extra strength of ultra formulations, we multiplied the size of ultra UPCs by a factor of 1.5 in our analysis to obtain equivalent sizes in relation to nonultra product variants. We then aggregated sales over UPCs to the product variant level. This aggregation gives us 74 variants and an average of 35 variants each quarter.

Second, we discuss the marketing-mix variables. In addition to product characteristics, we include the retail price, the availability of a sales promotion during a week, new product introductions, and the level of advertising. We operationalize the price variable as the weighted (by unit sales) average price per ounce of all the UPCs in the variant. The UPCs in each variant were priced and promoted similarly, as evidenced by the high correlation in their prices (>.8). Because the promotion variable is not accurately recorded in the Dominick's Finer Foods database, we follow Ailawadi, Kopalle, and Neslin's (2005) recommendation for measuring the promotion variable. Specifically, we consider a UPC promoted in a week if the net price is at least 5% lower than the maximum price paid in the previous four weeks and the subsequent four weeks. In line with the work of Chintagunta (2002), we define the sales promotion variable for a product variant as the proportion of UPCs in the product variant that were available on a sales promotion that week. In addition, we use a one-period lagged promotion variable to account for the purchase acceleration that may have occurred in the previous period due to a promotion.

We define the new product introduction variable for a product variant as the percentage of UPCs in the product variant that were new. In defining a UPC as new, we considered only the UPCs that corresponded to new product formulations and not those that corresponded to new package sizes and price packs. The new product introduction variable in the model allows for sales of a newly introduced UPC to be different from its long-term sales. Introductory sales may be higher because of novelty effects of a new introduction that generates trial. Alternatively, introductory sales may be lower because of a lack of awareness or initial acceptance. To minimize the latter effect, we treat a UPC as new for a period of 26 weeks (two quarters) after its initial introduction.[6] Because the average purchase cycle for these categories is less than 13 weeks, 26 weeks provides sufficient time for many consumers to try the new product. For the advertising variable, because weekly advertising data were unavailable, we inferred weekly advertising expenditure from monthly data by assuming that the brands allocate their advertising budgets evenly across the weeks of a month. Jedidi, Mela, and Gupta (1999) make a similar assumption in determining weekly advertising expenditures from quarterly data. To capture the diminishing effect of advertising, we use a logarithmic transformation, ln(1 + Ad), which we defined for zero values of advertising, and we measure Ad in thousands of dollars.

Third, we discuss the share of the no-purchase alternative by consumers. The estimation of the Stage 1 model requires the calculation of a no-purchase or outside alternative by consumers. On the basis of information from Information Resources Inc.'s *Marketing Fact Book*, we assume that each household consumes four ounces of dish detergent every week, and then we multiply the store traffic in a week by the weekly consumption rate to define the market size. We then subtract the sales of the brands under consideration to compute the "sales" of the no-purchase alternative. We then compute the respective shares from the sales of the brands and the market size. This approach is similar to that which Chintagunta (2002) uses. For the toothpaste category, we assume that each household consumes four ounces of toothpaste every week.[7] In our model, we assume that the utility of the outside good is affected by holidays and seasonal events. We use a dummy indicator variable to capture the influence of holidays and special events. To capture store-level differences, we use store-level demographic variables, such as the median income (INCOME), percentage of population over the age of 60 (AGE60), and the percentage of population that is black or Hispanic (ETHNIC). In addition, we capture the effect of store-specific retail competition by using the distance of the store from two major competitors, Cub Foods and Omni.

Finally, we discuss the instrumental variables. We correct for endogeneity of price through the use of wholesale prices interacted with brand and other attribute dummies as instrumental variables. We treat the product attributes, new product introductions, advertising, and sales promotions as exogenous in the Stage 1 model. Because we expect that the time frame for decisions on product attributes and new product introductions is much longer than a quarter, these decisions are unlikely to be correlated with the weekly unobservables and therefore can be considered exogenous. Similarly, we treat sales promotions as exogenous because, in general, such decisions are made on a quarterly basis and often require a lead-time of several weeks for effective implementation (see Chintagunta 2002). For similar reasons, we treat advertising as exogenous for the Stage 1 model.

The Stage 2 model. Recall that we estimate brand equities on a quarterly basis in Stage 1. Thus, to infer the effects of advertising, sales promotions, and product innovations on brand equity, we need to operationalize quarterly measures of these variables. As in the Stage 1 model, we use a logarithmic transformation of advertising. We define the quarterly sales promotion variable as the proportion of UPCs of the brand that were on promotion during that quarter. We operationalize the product innovation variable as the fraction of UPCs of the brand that were new in that quarter.

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[6] Recall that Mentadent was introduced as a new brand during the period of our analysis. Because our product innovation variable should capture the effect on existing brands, we did not include the new UPCs involved in the launch of Mentadent in the product innovation variable.

[7] We estimated the model with alternative assumptions of the consumption rate at 200% or 80% of the assumed rate. The brand equity estimates are robust to these alternative assumptions.

To control for endogeneity of the quarterly advertising and quarterly sales promotion variables, we use lagged values of advertising and sales promotions, lagged sales, lagged competitive advertising, and sales promotions as instrumental variables. We use a logarithmic transformation of lagged advertising and lagged sales in constructing our instruments. We define the competitive advertising variable as the logarithm of the combined advertising expenditures of all the competitors. The competitive sales promotion variable is the proportion of the combined volume sales of all the competitors on deal in that quarter. As in the Stage 1 model, we interact these instruments with brand-specific dummies. We treat product innovations as exogenous for reasons similar to those in the Stage 1 model.

Results and Discussion

Stage 1 Results: Brand Equity Estimation and Tracking

We assess the reliability of the brand equity estimates by randomly dividing the stores into two samples and estimating the brand equities in each.[8] The correlations between the estimated brand equities across the two samples were .93 and .96 for the toothpaste and the dish detergent categories, respectively. The high correlations suggest that the brand equity estimates are reliable.

For our data observation window, Table 2, Panel A, and Table 3, Panel A, present the estimates from the Stage 1 model for the toothpaste and dish detergent categories, respectively. First, for the toothpaste category, Table 2, Panel A, reveals that, on average, consumers prefer paste (to gel), medium sizes, and toothpaste without baking soda but with peroxide. As we expected, the mean price coefficient is negative, and the promotion coefficient is positive. The corresponding average own-price elasticities of the toothpaste brands range from –1.21 to –.85. These price elasticity estimates are similar to those of Tellis (1988b). The lag promotion parameter is negative, implying that temporary promotion of a product reduces its preference slightly in the following week, potentially due to purchase acceleration. The direct effect of advertising on utility is statistically not significant, whereas that of new product introductions is positive and significant. The statistically nonsignificant effect of advertising in the Stage 1 model is not surprising, because prior studies (e.g., Tellis 1988a) have found weak short-term advertising effects (these are weekly effects in our Stage 1 model). Among the heterogeneity parameters, only those that correspond to A&H brand equity and price sensitivity are statistically significant.

We now turn to the mean brand equity estimates for the toothpaste category, which we averaged across all quarters (see Table 2, Panel B). The second column of Table 2, Panel B, reveals that among toothpaste brands, Mentadent has the highest mean equity followed by A&H and Crest. It is noteworthy that Mentadent and A&H have high brand equities when neither brand has a high market share. This indicates that the buyers of the two brands derive high utility from the respective brand names, after we partial out the effects of marketing-mix variables. Notably, the high brand equity estimates of the two brands square well with the price premiums they enjoyed with respect to other brands (see Table 1, Panel A). The price premiums these brands enjoy may be an indicator of what consumers are willing to pay for the brand, a metric that Aaker (1996, p. 321) considers the single most important indicator of brand equity.

Second, for the dish detergent category, Table 3, Panel A, reveals that, on average, consumers prefer dish detergents without lemon scent but that are antibacterial, and they prefer the ultra version of dish detergents. As we expected, the price coefficient is negative, the promotion coefficient is positive, and the lag promotion effect is negative. As in the toothpaste category, the direct effect of advertising on mean utility is statistically not significant, and that of new product introduction is positive and significant. The average own-price elasticities for brands in this category range from –3.45 to –3.06. Although these elasticity estimates agree with Tellis's (1988b) results, they are higher (in magnitude) than the corresponding estimates for the toothpaste brands, suggesting a lower level of brand differentiation in the dish detergent category. However, unlike in the toothpaste category, none of the heterogeneity parameters are statistically significant.

In Table 3, Panel B, we present the mean brand equity estimates averaged across all quarters for the dish detergent brands. Table 3, Panel B, reveals that Dawn has the highest mean equity followed by Palmolive. Unlike the toothpaste category, the rank order of the brands on equity is consistent with their rank order based on market shares. Unlike in the toothpaste category, however, no niche brands command a significant price premium in this category.

Validating the brand equity measures. We assess the validity of the brand equity measure by estimating its correlations with other measures of brand equity that have been proposed in the literature, such as price premium, sales premium, and revenue premium. Because we estimate brand equity with respect to the store brand, we compute the premium measures also with respect to the store brand. The computed correlations of the brand equity measure with price premium, sales premium, and revenue premium are .707, .207, and .313, respectively, in the toothpaste category. The corresponding numbers for the dish detergent category are .386, .747, and .786. All correlations are statistically significant ($p < .01$). Thus, in both categories, the brand equity measure shows positive and statistically significant correlations with the other measures of brand equity. However, there are notable differences in the correlations of the intercept measure with other individual measures and across the two categories. For example, in the toothpaste category, the intercept brand equity measure displays smaller positive correlations with sales and revenue premiums than with price premium. This difference in correlation highlights the difference between the firm-based measures, such as sales and revenue premiums, that are correlated with market share and the consumer-based mea-

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[8] Considering the substantial amount of time it takes to estimate the full model with heterogeneity, we estimated the brand equities for the two samples assuming homogeneity and thus employed two-stage least squares.

TABLE 2
Summary of Stage 1 Results for the Toothpaste Category

A: Estimates from the Stage 1 Model

Parameter	Estimate	SE	t-Value
Gel	–.755	.013	–60.023
Baking soda	–1.000	.037	–27.027
Peroxide	.349	.025	14.024
Medium[a]	.484	.029	16.647
Medium-large[a]	.614	.014	43.229
Large[a]	–.200	.017	–11.764
Extra large[a]	–.316	.077	–4.127
Price	–5.968	.759	–7.859
Promotion	.469	.063	7.403
Lagged promotion	–.099	.045	–2.226
New product introduction	.230	.107	2.157
Advertising	.000	.0001	–.086
Special events	–.019	.110	–.172
Age 60	–1.224	.259	–4.720
Ethnic	.237	.534	.445
Income	.328	.164	1.996
Household size > 5	–2.663	3.043	–.875
Distance from nearest Cub store	.012	.007	1.656
Distance from nearest Omni store	.018	.014	1.312
Heterogeneity Parameters			
A&H (SD)	2.242	.353	6.350
Aquafresh (SD)	.089	36.550	.002
Close-Up (SD)	.147	10.209	.014
Colgate (SD)	.025	8.339	.003
Crest (SD)	.087	2.750	.032
Mentadent (SD)	.041	4.923	.008
Price (SD)	2.977	1.715	1.736

B: Mean Brand Equity Estimates Averaged Across Quarters

Brand	Mean Brand Equity Across Quarters
A&H	2.359
Aquafresh	1.225
Close-Up	.580
Colgate	1.577
Crest	2.189
Mentadent	3.377

[a] We set the dummy variable for small to zero.

sures, such as the intercept measure and price premiums, that reflect the value the buyers of a brand place on the brand name regardless of its market share.

In contrast, the correlations of the intercept brand equity measure with sales and revenue premiums are high in the dish detergent category. The rationale for this difference is that the toothpaste category has some niche brands (i.e., Mentadent and A&H) that are highly valued by their respective focused target markets, unlike the dish detergent category in which the brands do not appear to be highly differentiated. Overall, the positive, significant, and moderately high correlation of the intercept brand equity measure with other measures of brand performance, especially price premium, provides confidence that this is a valid measure of brand equity.

Time trend in brand equity. We now turn to the time trend in the brand equities, which should be of interest to the managers who monitor brand health. For the toothpaste category, we present the brand equity estimates over time in Figure 1, Panel A, and summarize the number of quarters when these brands experienced statistically significant and positive and negative deviations in their equity compared with the values in the first quarter in Table 4, Panel A.[9] Figure 1 reveals that the brand equities of all brands, with the exception of Mentadent, appear to have decreased compared with the values in the first few quarters. From Table 4, Panel A, it is clear that most of these deviations are statistically significant. The narrowing differences between the national brands and the store brand point to an overall commoditization of the category. However, the brand equities of

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[9] In the toothpaste category, the store brand enters the market in the third quarter of 1990. Because we estimate the brand equities with respect to the store brand, henceforth, we track brand equities.

TABLE 3
Summary of Stage 1 Results for the Dish Detergent Category

A: Estimates from the Stage 1 Model

Parameter	Estimate	SE	t-Value
Ultra	.246	.020	12.384
Lemon scent	–.625	.007	–84.020
Antibacterial	–.459	.023	–19.660
Small[a]	.710	.137	5.193
Medium[a]	.652	.013	49.432
Medium-large[a]	.221	.016	13.992
Large[a]	.331	.012	27.211
Price	–8.545	3.227	–2.648
Promotion	.276	.021	13.022
Lagged promotion	–.164	.023	–7.262
New product introduction	.159	.018	8.869
Advertising	.005	.007	.772
Special events	–.025	.038	–.654
Age 60	2.198	.336	6.535
Ethnic	–1.075	.585	–1.839
Income	–10.254	2.704	–3.793
Household size > 5	–.163	.408	–.400
Distance from nearest Cub store	–.181	.037	–4.910
Distance from nearest Omni store	.167	.025	6.784
Heterogeneity Parameters			
Ajax (SD)	.863	2.754	.313
Dawn (SD)	.474	.758	.626
Ivory (SD)	2.013	1.716	1.173
Joy (SD)	.106	7.878	.014
Palmolive (SD)	.620	.769	.806
Sunlight (SD)	.941	1.142	.824
Price (SD)	2.282	1.954	1.168

B: Mean Brand Equity Estimates Averaged Across Quarters

Brand	Mean Brand Equity Across Quarters
Ajax	.452
Dawn	1.566
Ivory	1.100
Joy	1.007
Palmolive	1.403
Sunlight	.864

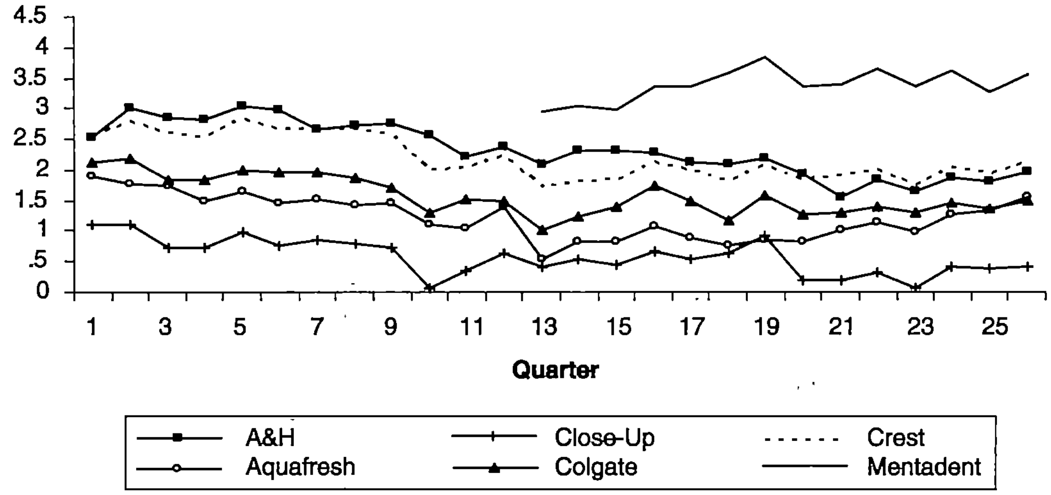
[a] We set the dummy variable for the extra-large size to zero.

most of the brands appear to rebound from their low point around Quarter 13 (fourth quarter of 1995), which coincides with Mentadent's entry. Further examination of the data reveals that during this time frame, established brands introduced a flurry of product innovations (e.g., baking soda, peroxide, new flavors, stand-up packaging). This appears to allow them to recover some of their equity and to put some distance between themselves and the store brand.

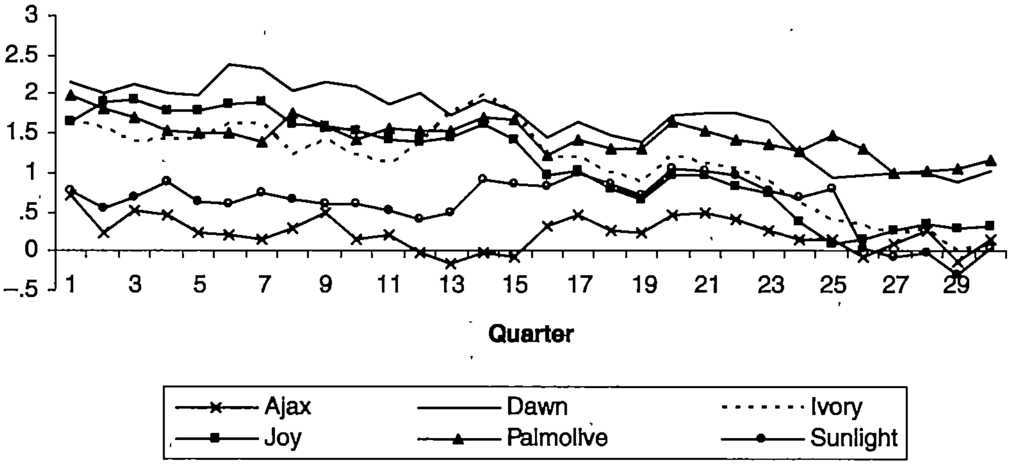
To quantify the net effect of the changes in brand equity, we simulated the sales of each brand such that its brand equity remained the same, average value in the first four quarters. We retained the equities of the remaining brands at their current levels during this simulation. We then compared these simulated sales with the actual sales of the brand. The total difference between the two values across all the quarters is a measure of the effect of changes in brand equity. If the actual sales are lower than the simulated values, it implies that the brand has lost sales because of a decline in brand equity. We present the results from this simulation for the toothpaste brands in Table 4, Panel B. The results confirm that with the exception of Mentadent, all toothpaste brands lost some sales because of changes in brand equity. In terms of magnitude, although the larger brands, Crest and Colgate, seem to have lost the most, in terms of percentage, A&H is the biggest loser. Part of the reason behind the decline in A&H's equity is a significant reduction in advertising support for this brand over time. As we discuss subsequently, our Stage 2 model reveals that advertising is an important driver of brand equity. Furthermore, our analysis of the time trend in A&H's brand equity reveals that the brand was adversely affected by the introduction of baking soda toothpaste by other brands, which

FIGURE 1
Brand Equity Estimates

A: Toothpaste Brands



B: Dish Detergent Brands



diluted its unique selling proposition. We discuss the tracking of A&H's brand equity in more detail subsequently.

For the dish detergent category, we present the brand equity estimates over time in Figure 1, Panel B, and summarize the number of quarters with statistically significant deviations in brand equity in Table 5, Panel A. The results in Table 5, Panel A, reveal that as in the toothpaste category, the deviations in brand equity are statistically significant. Moreover, most of the statistically significant deviations are negative in magnitude. Indeed, the trends in brand equities in Figure 1, Panel B, reveal declining equities and declining differences between brands. These trends suggest decreasing brand differentiation in the category. The results also reveal a significant declining trend in the brand equities of Ivory and Joy, both of which are Procter & Gamble brands. The market shares of both brands declined substantially during this period. Ivory's share dropped more steeply from 18.4% in the fourth quarter of 1989 to 5.8% in the first quarter of 1997, and Joy's share dropped from 13.1% to approximately 10.5% during the same period.

As in the toothpaste category, we quantified the net effect of changes in brand equity for the dish detergent brands by comparing the actual sales with the simulated sales and by holding the brand equity the same as in the first year. The results appear in Table 5, Panel B. The results reveal that all brands lost sales because of declining brand equity over time. The results also confirm our observation that the three Procter & Gamble brands—Dawn, Ivory, and Joy—dropped significantly in their brand equities during this period. However, the biggest loser among these brands both in terms of magnitude and as a percentage of sales was Joy. Conversely, Sunlight lost the least in terms of magnitude and percentage of sales.

TABLE 4
Temporal Changes in the Equity of Toothpaste Brands

A: Number of Quarters with Brand Equity Estimates Significantly Different from the First Quarter

Brand	Number of Quarters Compared	Number of Quarters with Significant Deviations	Number of Quarters with Positive, Significant Deviation	Number of Quarters with Negative, Significant Deviation
A&H	25	20	4	16
Aquafresh	25	23	0	23
Close-Up	25	23	0	23
Colgate	25	21	0	21
Crest	25	23	6	17
Mentadent	13	6	5	1

B: Effect of Change in Brand Equity for Toothpaste Brands

Brand	Effect of Change in Brand Equity on Sales (oz.)	As a % of Total Sales	Effect of Change in Brand Equity on Revenue ($)	As a % of Total Revenue
A&H	–363,849	–62.72	–194,191	–65.84
Aquafresh	–473,775	–51.12	–189,073	–52.91
Close-Up	–122,427	–23.37	–45,945	–25.84
Colgate	–940,233	–38.72	–345,947	–40.91
Crest	–1,202,316	–34.75	–465,605	–36.16
Mentadent	82,606	28.57	59,209	27.78

Stage 2 Results: The Effects of Marketing Actions on Brand Equity

We infer the effects of advertising, sales promotions, and product innovations on brand equity by pooling the brand equity estimates from the Stage 1 model and estimating the model in Equation 4 separately for each of the two categories.[10] We present these results for the two categories in Table 6.[11]

Our results are fairly consistent in terms of the impact of marketing actions on brand equity across the two categories. The lagged brand equity coefficient, a measure of the stability or inertia in brand equity, is equal to .905 for the dish detergent category and .945 for the toothpaste category. Clarke (1976) finds that the quarterly carryover coefficient in the case of sales is approximately .6. The higher carryover for brand equity is consistent with our expectation that brand equity should exhibit higher inertia. The advertising coefficients in both categories have the expected positive sign and are significant both in the short run and in the long run. Sales promotions have a negative effect on brand equity in both categories. However, the effect is not statistically significant either in the short run or in the long run. As we expected, the innovation variable has a significant, positive effect on brand equity in the toothpaste category both in the short run and in the long run. However, the effect is not significant in the dish detergent category. This may be because all competitors quickly matched the principal innovation of ultra formulation.

The consequence of high inertia in brand equity is that the long-term effects of advertising, sales promotions, and product innovations are much higher in magnitude than are the short-term effects. For example, in the toothpaste category, the long-term effect is more than 20 times that of the corresponding short-term effect. Thus, inferring the total impact of marketing actions on brand equity only on the basis of the immediate effect will significantly underestimate their total impact.

To understand the extent to which the different marketing-mix variables affect brand equity, we computed the contribution of the variables in explaining variation in brand equity. In both the categories, we find that lagged brand equity explains a significant portion of the variation in brand equity (86.3% of the variation in toothpaste and 90.5% in dish detergents). Although advertising (8.9%) explains most of the remaining variation in brand equity in the dish detergent category, all three variables—advertising, sales promotions, and product innovations—explain approximately equal portions of the remaining variation for toothpaste brands.

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[10] To assess the appropriateness of the partial adjustment model specified in Equation 4, we test for the autocorrelation of errors for the individual brands using Durbin's h statistic, which is the appropriate test in the presence of a lagged dependent variable. We performed this test assuming that the marketing variables were exogenous. In the toothpaste category, of the six regressions (one for each of the six brands), only one exhibited significant autocorrelation. In the dish detergent category, none of the brand equities exhibited autocorrelation. Thus, in general, our data are consistent with the partial adjustment model. Furthermore, we performed a test based on the work of Johnston (1984, p. 347) to check whether advertising, sales promotions, and product innovations have the same decay parameter. We could not reject the null hypothesis that the decay parameters are the same for the three marketing-mix variables in both the categories.

[11] Our Stage 2 results are fairly consistent in terms of the effect signs across different estimation methods, such as ordinary least squares and two-stage least squares, which suggests robustness.

TABLE 5
Temporal Changes in the Equity of Detergent Brands

A: Number of Quarters with Brand Equity Estimates Significantly Different from the First Quarter

Brand	Number of Quarters Compared	Number of Quarters with Significant Deviations	Number of Quarters with Positive, Significant Deviation	Number of Quarters with Negative, Significant Deviation
Ajax	29	29	0	29
Dawn	29	24	2	22
Ivory	29	25	2	23
Joy	29	25	5	20
Palmolive	29	29	0	29
Sunlight	29	21	13	8

B: Effect of Change in Brand Equity for Dish Detergent Brands

Brand	Effect of Change in Brand Equity on Sales (oz.)	As a % of Total Sales	Effect of Change in Brand Equity on Revenue ($)	As a % of Total Revenue
Ajax	–472,334	–17.99	–26,191	–19.43
Dawn	–4,976,301	–34.73	–300,960	–32.79
Ivory	–2,825,991	–40.94	–157,431	–36.48
Joy	–5,910,465	–90.42	–303,063	–74.93
Palmolive	–3,063,835	–24.26	–189,239	–23.88
Sunlight	–355,557	–4.87	–20,326	–5.56

Managerial Implications

An Illustrative Application of Tracking Brand Equity: The Case of A&H

The case of A&H in the toothpaste category illustrates the strategic lessons that may be learned from tracking brand equity. Recall that A&H was introduced with a unique formulation of baking soda and commanded a significant price premium. Furthermore, our analysis of the net effect of changes in brand equity for the toothpaste category revealed that this brand lost the most as a percentage of sales because of a decline in brand equity. In Figure 2, we present the "observed" brand equity as estimated from the Stage 1 model along with a 90% confidence band of the brand equity that the Stage 2 model would predict. Thus, points within the confidence band represent observed brand equity values that can be explained with some confidence by A&H's marketing actions as well as measurement errors and "white noise" in the brand equity estimates. Conversely, points outside the confidence band may require further investigation because they cannot be well explained by systematic factors.[12]

In the case of A&H, for example, the "observed" Stage 1 brand equity estimates fall within the confidence band in all but three cases. These deviations warrant a brief discussion. Note that the three significant adverse deviations marked 1, 2, and 3 coincided with competitive new product introductions: (1) entry of Colgate baking soda toothpaste, (2) entry of Crest baking soda toothpaste, and (3) entry of Mentadent baking soda and peroxide toothpaste, respectively. These imitations of the baking soda attribute challenged the unique identity of A&H as the toothpaste with baking soda and, thus, its ability to differentiate itself. Notably, the market share of this brand did not record a perceptible decline during this period. However, judging from the trend in the proportion of volume sold on deal, we infer that A&H was able to maintain its market share by resorting to promotional deals. Thus, an analysis of market share alone may not reveal the true health of a brand. This case

TABLE 6
Effect of Marketing Actions on Brand Equity

	Toothpaste Category	Dish Detergent Category
Intercept	.054	.079
	(.65)	(2.05)
Lag brand equity	.945	.905
	(31.36)	(36.57)
Advertising	.016	.018
	(1.90)	(2.80)
Sales promotions	–.098	–.005
	(–1.103)	(–.043)
Innovations	.246	22.596
	(1.96)	(.26)
Long-Term Effects		
Advertising	.287	.184
	(1.94)	(3.90)
Sales promotions	–1.78	–.052
	(–1.139)	(–.043)
Innovations	4.486	236.745
	(1.79)	(.25)
R^2	.92	.907
Adjusted R^2	.918	.905

Notes: t-values are in parentheses.

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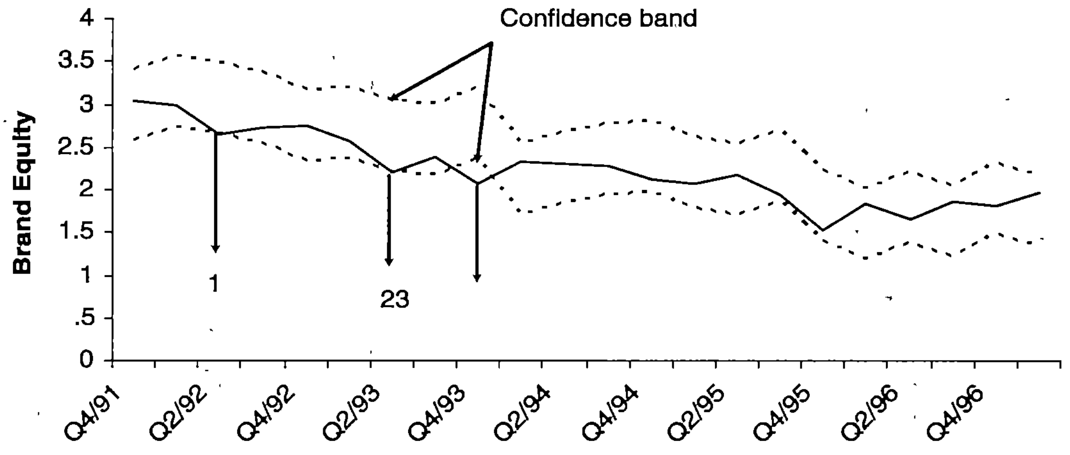
[12] Although we used data from all quarters to draw up the confidence band for convenience, in practice, confidence bands are based on historical data up to the previous quarter.

FIGURE 2
Brand Equity of A&H



Notes: For example, Q4/91 = Quarter 4 in 1991.

also indicates that brands that build their equity on imitable attributes will find it difficult to defend themselves against competitors. Thus, brands need to constantly innovate to maintain and enhance their equity, at least in dynamic markets such as toothpaste.

Overall, the A&H illustration reveals that the tracking of brand equity has a useful diagnostic value. It can help the brand's managers monitor the long-term health of a brand by tracking the impact of a firm's actions and competitive marketing programs on the brand's equity. Next, we illustrate how a manager may use the model to understand the relative desirability of alternative marketing actions to influence brand equity.

Performing "What-If" Analyses of Alternative Marketing Actions

We take the perspective of A&H's brand equity manager to illustrate the managerial analyses that can be conducted using the model results. We assume that at the beginning of Quarter 23, the brand equity manager is interested in exploring alternative marketing actions to achieve brand equity targets at the end of the year. Specifically, we assume that the manager is considering alternative targets of 5% and 10% increases in brand equity by the end of Quarter 26 from the average of 1.88 in Quarters 19–22. Although planning for brand equity may typically entail a planning horizon of more than one year, for simplicity, we assume a one-year horizon. We then address the following questions: (1) What annual advertising budget uniformly spent in each of Quarters 23–26 will achieve the brand equity targets? and (2) How does the introduction of new products reduce the advertising expenditure needed to achieve the brand equity targets? We answer these questions with the help of the Stage 2 model. For this analysis, we assume that the promotions will be used at the same level as in the previous year. Moreover, new product introductions, if applicable, are assumed to be uniformly introduced during the year. Because we assume that a new product requires two quarters to be fully established, uniform new product introductions entail an equal number of product introductions every two quarters. Appendix B describes the procedure we used to answer our two questions, and Table 7, Panel A, shows the results of the analysis. In deriving the table, for simplicity, we use the Stage 2 model estimates from the data on all quarters.

The analysis shows that with no new product introductions, an annual advertising spending of $15.6 million is needed to increase the brand equity by 10% in one year. As a comparison, the average annual spending of A&H during the data observation window was $9 million, whereas advertising spending dropped to zero during the year before Quarter 23. If the targeted improvement is 5%, Table 7, Panel A, shows that the advertising expenditure needed decreases significantly to $2.4 million. The steep increase in advertising expenditure needed to achieve the higher brand equity target is due to the diminishing returns to advertising at higher levels.

Although the advertising expenditure needed for achieving the higher brand equity target appears to be high compared with historic spending levels by A&H, Table 7, Panel A, shows that the beneficial effect of new product introductions on brand equity can significantly reduce the spending levels needed. Moreover, the dollar reductions in advertising needed are more substantial when the targeted increase in brand equity is higher. Thus, product innovations may be particularly more effective and efficient in achieving a significant than a marginal brand equity improvement. Note that the calculations in Table 7, Panel A, do not consider the direct payoffs (or risks) from the introduction of new products. Prior studies (e.g., Urban and Hauser 1993) have shown that new products have significant potential to generate profits but also carry significant risks. Instead, Table 7,

TABLE 7
Profit Impact of Alternative Policies

A: A&H: Advertising Spending and Innovation Levels to Achieve Brand Equity Targets

Number of New Product (UPC) Introductions Every Six Months	Annual Advertising Expenditure to Achieve 5% Brand Equity Target ($)	Annual Advertising Expenditure to Achieve 10% Brand Equity Target ($)
0	2,400,000	15,600,000
1	2,100,000	13,600,000
2	1,900,000	12,000,000
3	1,400,000	10,800,000
4	1,300,000	9,200,000

B: A&H: Expected Quarterly Profit Impact of Increasing Brand Equity

	Increase in A&H's Quarterly Profit		
	No Competitor Brand Equity Improvement	5% Improvement in Key Competitors' Brand Equity	
Targeted Brand Equity Improvement for A&H	Scenario A	Scenario B	Scenario C
0%	—	—	–$1,034,000
5%	$1,486,000	$ 372,000	—
10%	$3,083,000	$1,885,000	—

Panel A, captures only the beneficial affects of new product introduction in reducing advertising spending needed to boost brand equity. The brand equity manager can point to the advertising savings as an additional benefit in any analysis of new product introductions.[13]

In recommending brand equity targets, the brand equity manager will be expected to address the profit consequences of improving brand equity. As we discussed in the "Literature Review" section, measuring the profit implications of increasing brand equity can be a difficult task because high equity can be potentially leveraged with profitable new products that are currently not offered by anyone (Keller 1998). Moreover, the benefit from an increase in brand equity may depend on competitive actions. Thus, we restrict ourselves to analyzing the impact of brand equity improvements on profit and assume no change in the product variants offered by A&H and its competitors. Furthermore, we calculate the quarterly profit increase for A&H by assuming that the advertising and promotion level for each brand is equal to the corresponding average value in the year ending in Quarter 22. Because new product introductions can vary significantly from year to year, for simplicity, we assume no product introductions for any competitor. We run simulations using the Stage 1 model for calculating the profit impact of an increase in A&H's brand equity, assuming that the marginal cost constitutes 30% of the wholesale price, as do Jedidi, Mela, and Gupta (1999). To examine the impact of competitive actions to improve brand equity, we examine two scenarios: (1) Competitors' brand equities remain the same as in Quarter 22, and (2) the brand equities of the largest competitors—Aquafresh, Colgate, and Crest—increase by 5%, possibly because of advertising or new product introductions on their part.

The results of this analysis in Table 7, Panel B, show that a 5% brand equity improvement increases A&H's quarterly profit by $1.5 million under the first scenario. Considering the advertising expenditure needed to achieve the 5% brand equity increase under various new product introduction scenarios (see Table 7, Panel A), payback can be achieved within two quarters.[14] Conversely, the 10% improvement in brand equity has a much less favorable payback. Thus, these results indicate that improvements in brand equity can be profitable but that a gradual improvement in a given time horizon may be more profitable than a drastic improvement. The intuition is that a drastic improvement requires a high intensity of advertising expenditure, which diminishes profit. This suggests that brand equity should be managed with a long-term planning horizon because improving brand equity in a short time frame may be prohibitively expensive. Conversely, both panels in Table 7 (the first scenario) show that significant improvements in brand equity over a short time frame may be best achieved with the help of new product introductions because the payback period may be more favorable under these conditions.

We observe in Table 7, Panel B, that under the second scenario, when competitors make brand equity improvements, A&H's quarterly profit gains from brand equity improvements are significantly reduced. However, this does not imply that A&H should not undertake brand equity improvement when its largest competitors increase their brand equities by 5%. Note that the profit gains reported under the second scenario are in comparison with the first scenario when none of the competitors improve their brand equity. For decision-making purposes, the relevant base of comparison for the results under the first scenario is the change in profit under a third scenario, in which Aquafresh, Colgate, and Crest improve their brand equities by 5% but A&H undertakes no improvement in its brand equity. The results for the third scenario, which we report in Table 7, Panel B, show that A&H will experience a substantial reduction in profit if it chooses not to improve its brand equity when its competitors increase their brand equity by 5%. Thus, anticipated competitive improvements in brand equity strengthen the brand equity manager's case for improving A&H's brand equity.

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[13] Note that new product introductions typically involve an increase in advertising spending to create awareness. This spending enters into the cost–benefit calculation for introduction of the new product. However, the advertising savings we discuss here pertain to brand-image-oriented advertising, which is distinct from introductory advertising.

[14] This assumes that the brand equity is maintained at the new level over the payback period. Our estimated Stage 2 model suggests that advertising expenditures of $300,000 per quarter can sustain the brand equity at the new higher level

To summarize, we show how a brand equity manager can use the model results to perform what-if analyses of alternative marketing actions for achieving brand equity targets. We also show how the Stage 1 model can be used to understand the profit implications of brand equity targets. Our substantive results for the case of A&H show that the beneficial effect on brand equity due to new product introductions can significantly reduce the need for advertising investments. In particular, new product introductions may be a more efficient tool when a firm aims to improve brand equity drastically. However, in general, it may be more profitable to plan for gradual brand equity improvements over a longer planning horizon.

Implementation Issues

We now address some practical issues in implementing our methodology in a real-world setting. Although we had store-level data from a single chain (account data in practitioner parlance; see Bucklin and Gupta 1999), some practitioners may have access only to data from a national or regional panel of stores that belong to different chains. In such a case, the analyst must examine multiple store brands, none of which are available in all stores. In this case, we recommend the measurement of brand equity with reference to a national brand. Another practical issue pertains to the length of time for which historic data needs to be gathered. In our analysis, we used a long time series because of our interest in analyzing historical changes in brand equity. Without such a need, monthly data do not need to go back further than two years for implementing our tracking framework.

Conclusion

Our analysis reveals that reliable estimates of brand equity can be obtained from store-level sales data, which marketing practitioners in packaged goods firms often use to monitor a brand's performance, estimate price elasticities, and perform various other analyses (Bucklin and Gupta 1999). The brand equity estimates can then be combined with more conventional performance measures, such as market share and distribution coverage, to formulate marketing programs. Firms employing customer surveys to monitor brand equity can use the approach we present herein to monitor brand equity values that are derived from customer purchase versus attitudinal data. Multiple measures of brand equity based on different data sources can offer reinforcing and unique insights into a brand's competitive market position.

We find that the intercept measure of brand equity effectively captures the high equity of strongly positioned popular brands and brands that command a significant price premium in niche markets. We argue that in the toothpaste category, popular brands, such as Crest and Colgate, may be able to exploit their higher equities in introducing new products to meet changing customer needs. Conversely, investments in maintaining and building brand equity on the part of niche brands, such as Mentadent and A&H, may pay off in terms of higher profitability through premium pricing, lower price elasticities, and lower promotion-to-sales ratios.

We use the case of A&H to illustrate how the tracking of brand equity can provide valuable insights for brand managers that may not be available from tracking market share or sales information. Our results from the calibration of the Stage 2 model in the toothpaste and dish detergent markets reveal a high level of inertia in brand equity estimates. Because of the high inertia, a brand potentially gains a longer window to respond to a competitive product or marketing program innovation. In the absence of a suitable response to the competitive innovation, however, the brand can experience cumulative erosion in brand equity that may be difficult to recover. Therefore, we suggest that brand managers should monitor a brand's equity in addition to sales, market share, and distribution coverage.

We show how our model results can be used to estimate the relative profitability of alternative marketing actions to boost brand equity. Substantively, we find evidence that advertising has a significant, positive effect on brand equity, whereas the effect of sales promotions is positive but not significant in both the toothpaste and the dish detergent markets. Moreover, our results indicate that the impact of advertising on brand equity exceeds that of promotions in magnitude. Given this finding and the evidence that decreases in brand equity may be difficult to recover because of high inertia, the shift in the recent years toward increased promotional budgets at the expense of advertising in consumer packaged goods deserves reconsideration.

Our empirical results indicate that product innovations can have a significant, positive effect on brand equity if they are meaningful to consumers; this appears to be the case in the toothpaste category. This finding has important implications because prior marketing literature has focused almost solely on the effects of advertising and sales promotion on brand equity. In view of management concerns about the productivity of advertising expenditures, it is important to pay attention to the entire marketing mix in an integrated way to understand the impact on brand equity. We find that product innovations can efficiently substitute for significant spending on image-oriented advertising. Indeed, we find that significant product innovations may be particularly useful for attaining drastic improvements in brand equity over a shorter period. Thus, marketing managers need to consider the impact of product innovations on brand equity while evaluating the trade-off between the potential costs and benefits of introducing new products. Conversely, brand equity managers need to go beyond advertising and packaging and view product innovations as an integral part of their strategy kit to manage brand equity.

We conclude with a few comments on the limitations of our study along with suggestions for further research. First, although we studied the impact of marketing-mix elements, such as product innovations, advertising, and sales promotions, on brand equity, our findings are based on the analysis of only two packaged goods markets. It would be useful to assess the relative importance of each of these elements in building brand equity across a larger set of product categories. Second, in the Stage 2 analysis, our results for the effects of advertising, sales promotions, and product innovations on brand equity are at the pooled (across-brands) level. We were constrained to estimate at the pooled level because of the small number of observations (quarters). However, a firm may be more interested in how the equity of its brand responds to marketing-mix variables than in an industrywide pooled estimate. It would be feasible to estimate the effect of marketing-mix actions on brand equity at the individual brand level if data were available from several regional markets. Third, we used advertising expenditure data to capture the effect of advertising on brand equity. If data on the specific advertising messages used were available, these could also be incorporated to provide additional insights. Furthermore, given precedence in the literature (e.g., Jedidi, Mela, and Gupta 1999; Mela, Gupta, and Lehmann 1997), we investigated the effect of absolute levels of advertising and promotion spending on performance measures, such as brand equity. However, in some markets, performance may depend on relative measures, such as share of voice, rather than the absolute levels. Fourth, although we used the brand intercept as a measure of brand equity, we recognize that there are different perspectives on how brand equity should be measured (see the "Literature Review" section). In particular, it may be useful to go beyond the intercept measure and study brand equity as a differential response to marketing variables (Keller 1998) by including brand-specific response variables. The challenge in doing so is to aggregate these many measures into a single overall measure of brand equity that managers may desire. Along similar lines, in addition to their effect on the intercept, marketing actions, such as advertising and promotions, can affect the slope coefficients, such as price sensitivity. Given our focus on brand equity and a need for parsimony, our analysis has been limited to studying the changes induced by these marketing actions on the intercept. Correspondingly, the implications regarding profitability need to be interpreted with some amount of caution. Finally, a disadvantage of the proposed approach is that if offers a somewhat limited understanding of the drivers of brand equity compared with survey-based approaches (Park and Srinivasan 1994; Rust, Lemon, and Zeithaml 2004; Srinivasan, Park, and Chang 2005). For example, survey data on consumer perceptions enable Park and Srinivasan (1994) to identify the component of brand equity that is derived from perceptions on product attributes that are superior to objective levels (see also Kamakura and Russell 1993). Understanding the magnitude of this attribute-based component in relation to the remainder (which is presumably based on intangible elements, such as brand image) of observed brand equity may provide additional insight into the sources of brand equity. Along similar lines, reliance on scanner data limits the types of marketing expenditures that can be studied (Rust, Lemon, and Zeithaml 2004). Thus, we recommend that brand equity measures from store-level data be used to supplement, but not replace, survey-based measures.

Appendix A

First, we address potential endogeneity of advertising and sales promotion using instrumental variables. Second, because the dependent variable is subject to measurement error due to estimation error of the Stage 1 brand equities, we employ the generalized least squares procedure (see Hanushek 1974) to obtain efficient estimates. In addressing these two issues and the random effects in the model, we must use a 3SLS procedure. However, the Stage 1 estimation error in lagged brand equity, which appears as an independent variable in Equation 4, will yield biased and inconsistent estimates if we do not account for it (Schmalensee and Joskow 1986). We follow the work of Schmalensee and Joskow (1986) and use an adjusted least squares (ALS) procedure to address this issue. Thus, we use an adjusted 3SLS estimator, which is a hybrid between 3SLS and ALS. The adjusted 3SLS estimate is given by the following:

$$\text{(A1)} \qquad \hat{\beta}_{A3SLS} = Q^{-1}X'\Psi^{-1}Z(Z'\Psi^{-1}Z)^{-1}Z'\Psi^{-1}Y,$$

where X is an N × K matrix of independent variables, some of which may be estimated from an earlier stage; Z is an N × R matrix of instruments; Y is an N × 1 vector of independent variables; and Ψ is an N × N matrix that incorporates information about the Stage 1 covariance matrix of the dependent variable Y. The matrix Q is given by the following:

$$\text{(A2)} \qquad Q = [X'\Psi^{-1}Z(Z'\Psi^{-1}Z)^{-1}Z'\Psi^{-1}X - \Gamma'\Psi^{-1}\Gamma],$$

where Γ is an N × K matrix such that $\Gamma'\Gamma$ will yield a K × K matrix and the element that corresponds to lagged brand equity (second row and second column of the $\Gamma'\Gamma$ matrix) will be equal to the trace of the covariance matrix obtained from the Stage 1 estimation. This is true because we assume that among the independent variables, only lagged brand equity is measured with error. The second term on the right-hand side of Equation A2 adjusts for the bias due to the Stage 1 standard errors. In the absence of this correction, it is easy to verify that this estimator is similar in structure to the traditional 3SLS estimator. The covariance matrix of this estimate is as follows:

$$\text{(A3)} \qquad V(\hat{\beta}_{A3SLS}) = Q^{-1}[\hat{X}'(\hat{\sigma}^2 I + A)\hat{X} + H]Q^{-1},$$

where $\hat{X}$ are the predicted values of X using Z and $\hat{\sigma}^2$ is a consistent estimator of the variance of the error term. The K × K matrix H is given by $G'\hat{\beta}_{A3SLS}\hat{\beta}'_{A3SLS}G$, where G is a K × K matrix given by $\Gamma'\Psi^{-1}\Gamma$. We can obtain the N × N A matrix by multiplying the covariance matrix of the independent variable (lagged brand equity) by the square of the estimated value of this coefficient. Again, this simplification is possible because we have only one column of the X matrix measured with error. We use the scaled covariance matrix obtained from Stage 1. We estimate the model in two steps. In the first step, we obtain consistent estimates of the parameters by using adjusted two-stage least squares, accounting only for the endogeneity of advertising and sales promotions and the standard errors of the independent variables. Using these consistent parameter estimates, in the second step, we estimate the model using adjusted 3SLS by incorporating the standard errors of the dependent variable (see Hanushek 1974).

Appendix B

We define β_{00} and β_{04} as the current brand equity and the brand equity target, respectively, at the end of four quarters. Then, using Equation 4 recursively, we solve for the uniform quarterly advertising, Ad, needed to achieve the brand equity target as follows:

$$\text{(B1)} \qquad \text{Ad} = \frac{1}{\gamma_1}\left[\frac{\beta_{04} - \lambda^4\beta_{00}}{(1 + \lambda + \lambda^2 + \lambda^3)} - \gamma_0 - \gamma_2\text{Pr} - \gamma_3\text{In}\right].$$

In Equation B1, Pr and In are the assumed uniform innovation levels for A&H in each quarter. Equation B1 provides the natural logarithm of the quarterly advertising expenditure needed as a result of the logarithmic transformation of advertising we employed in the estimation.

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Don O'Sullivan & Andrew V. Abela

Marketing Performance Measurement Ability and Firm Performance

Marketing practitioners are under increasing pressure to demonstrate their contribution to firm performance. It has been widely argued that an inability to account for marketing's contribution has undermined its standing within the firm. To respond to this pressure, marketers are investing in the development of performance measurement abilities, but to date, there have been no empirical studies of whether the ability to measure marketing performance has any actual effect on either firm performance or marketing's stature. In this study of senior marketing managers in high-technology firms, the authors examine the effect of ability to measure marketing performance on firm performance, using both primary data collected from senior marketers and secondary data on firm profitability and stock returns. They also explore the effect of ability to measure marketing on marketing's stature within the firm, which is operationalized as chief executive officer satisfaction with marketing. The empirical results indicate that the ability to measure marketing performance has a significant impact on firm performance, profitability, stock returns, and marketing's stature within the firm.

"The effective dissemination of new methods of assessing marketing productivity to the business community will be a major step toward raising marketing's vitality in the firm and, more important, toward raising the performance of the firm itself" (Rust et al. 2004, p. 76). In response to the pressure on marketers to demonstrate their value to the firm, there have been several high-profile calls for more research in the area of marketing performance measurement (MPM) and several conceptual and empirical research papers (e.g., Donthu, Hershberger, and Osomonbekov 2005; Lukas, Whitwell, and Doyle 2005; Rust et al. 2004). Furthermore, there have been regular calls for marketing practitioners to develop and enhance their ability to account for marketing's contribution to firm performance (Ambler 2003; Bolton 2004). An assumption underlying these related academic and practitioner concerns is that developing and applying MPM ability leads to both greater status for marketing at the board level (see, e.g., Webster, Malter, and Ganesan 2005) and improved firm performance (Morgan, Clark, and Gooner 2002). However, to date, the relationship between MPM ability and either firm performance or marketing's stature within the firm has not been demonstrated empirically.

The primary purpose of this article is to test whether MPM ability contributes to actual firm performance or to marketing's stature within the firm, which we operationalize as chief executive officer (CEO) satisfaction with marketing. A secondary purpose is to explore two potentially distinct aspects of MPM ability: the ability to measure performance across a range of marketing activities (e.g., advertising, trade promotion, direct mail) and the ability to assess marketing performance using a comprehensive set of metrics (e.g., financial, nonfinancial).

We focus on firms in the high-technology sector. We chose high-tech firms because of the recognition that within this sector, marketing has been under intense pressure to demonstrate its contribution to firm performance. There are two primary reasons for this pressure. First, high-tech companies tend to have more of an engineering orientation than a marketing orientation, and thus top management tends to be more skeptical about the value of marketing (Davies and Brush 1997). Second, during the period we studied (early 2000s), the sector experienced the collapse of the "technology boom," which led to sharply increased scrutiny of marketing activities (Mohr and Shooshtari 2003). We begin by reviewing the MPM literature and generating several testable hypotheses.

Measurement and Performance

A long-standing caricature of marketing practitioners is that they love to spend money and hate to assess the results of that spending (e.g., Adler 1967). Marketers' inability to account for the function's contribution to firm performance is recognized as a key factor that has led to marketing's loss of stature within organizations (Kumar 2004; Lehmann 2004; Webster, Malter, and Ganesan 2005). This is reflected

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in increased demand for greater accountability (Doyle 2000; Morgan, Clark, and Gooner 2002; Rust et al. 2004). In addition, there have been several high-profile calls for more research in the area of MPM. Most notably, MPM topics have been consistently listed among the Marketing Science Institute's (1998, 2000, 2002, 2004, 2006) top priorities.

Marketing performance measurement is the assessment of "the relationship between marketing activities and business performance" (Clark and Ambler 2001, p. 231). Because the problem in question is the inability to account for marketing activities, our specific interest is in marketing's *ability* to assess this relationship. Given that the goal of MPM research is to demonstrate the value of the marketing activities, in line with the work of Rust and colleagues (2004), our focus is on marketing not as the "underlying products, pricing, or customer relationships" (Rust et al. 2004, p. 76) but rather as the "marketing activities" themselves, which we define as marketing communication, promotion, and other activities that represent the bulk of the typical marketing budget.

Marketing performance measurement research can be divided into three research streams: measurement of marketing productivity (e.g., Morgan, Clark, and Gooner 2002; Rust, Lemon, and Zeithaml 2004), identification of metrics in use (e.g., Barwise and Farley 2003; Winer 2000), and measurement of brand equity (e.g., Aaker and Jacobson 2001; Ailawadi, Lehmann, and Neslin 2002). Rust and colleagues (2004) build on the work of Srivastava, Shervani, and Fahey (1998) to describe a "chain of marketing productivity" that extends from marketing activities to shareholder value. Marketing activities influence intermediate outcomes (customer thoughts, feelings, knowledge, and, ultimately, behavior), which in turn influence financial performance of the firm. The MPM research we cited examines how marketers can measure the relationships along the chain of marketing productivity; which metrics firms use or could use along this chain, particularly financial, nonfinancial, and market-based assets; and contextual factors, particularly the firm's market orientation (e.g., Clark and Ambler 2001).

Underlying all this work is the assumption that such measurement effort is beneficial to the firm and is not just a post hoc justification of marketers' efforts—that improvements in marketing's ability to account for its activities will actually raise the performance of the firm. In the face of senior management demands that marketers demonstrate their value, the desire for justification is understandable. However, overcoming the inability to account for the function's contribution to firm performance requires that resources and management attention be expended on measurement efforts (Bonoma and Clark 1988). Incurring such cost assumes that the firm will benefit, and testing this assumption is the primary purpose of this article.

Hypotheses

We develop hypotheses based on a theoretical framework that links MPM ability to firm performance and CEO satisfaction with marketing. We begin by hypothesizing that MPM ability has an effect on actual firm performance. Sevin (1965) argues that the implementation of robust performance measures should result in greater marketing and firm performance. Several arguments that link MPM to improvements in marketing and firm performance have been advanced (see, e.g., Rust et al. 2004). First, anticipation of the scrutiny of marketing efforts will encourage greater attention to the activities that will be measured. The idea that "what gets measured gets done" is well founded in the management literature (see, e.g., Ouchi 1979) and is assumed within the MPM literature. Second, Webster, Malter, and Ganesan (2005) contend that marketing's contribution to the achievement of strategic goals is underrepresented in firms that do not measure marketing performance and that the performance of such firms may suffer as a result. Third, it has been argued that MPM should lead to learning, which should enable improved marketing decisions and, consequently, performance (Morgan, Clark, and Gooner 2002). Fourth, MPM offers performance feedback, and performance feedback has consistently been found to influence both managerial attitudes and behavior (Audia, Locke, and Smith 2000; Curren, Folkes, and Steckel 1992; Greve 1998; Miller 1994). Finally, feedback relative to goals has been demonstrated to produce strong effects (e.g., Locke and Latham 1990). Thus:

> H_1: MPM ability positively influences firm performance.

It has long been recognized that the marketing function typically plays a limited role in the process of strategy formulation (Anderson 1982; Day 1992; Webster 1992). Srivastava, Shervani, and Fahey (1998) argue that an important reason for this is that marketers struggle to measure and communicate to top management the impact of marketing activities on firm performance. Lehmann (2004) and Webster, Malter, and Ganesan (2005) observe that marketing has the greatest influence and stature in firms in which there are clear measures of marketing's contribution. Accordingly,

> H_2: MPM ability is positively associated with CEO satisfaction with marketing.

As we noted previously, although the primary purpose of this article is to test empirically whether MPM ability contributes to firm performance or to marketing's stature within the firm, a secondary purpose is to explore the ability to measure performance across a range of marketing activities and the ability to assess marketing performance using a comprehensive set of metrics. Although the two aspects are clearly related in that they both contribute to a firm's MPM ability, we hypothesize that they are distinct. For example, one firm may be able to measure the performance of its advertising or public relations (activities) only in terms of changes in awareness (nonfinancial metric), whereas another firm may be able to measure them in terms of revenue change (financial metric) and against specific goals and competitor performance (benchmark metric) (Ambler 2003).

The focus of the broader marketing accountability literature has been on the importance of the ability to measure disparate marketing activities (e.g., Rust, Lemon, and Zeithaml 2004; Webster, Malter, and Ganesan 2005). In addition, the discussion of MPM among practitioners has also tended to focus on the activities dimension (e.g., McMaster

2002). However, within the existing academic literature on MPM, the focus has tended to be on the metrics in use (e.g., Ambler, Kokkinaki, and Puntoni 2004; Barwise and Farley 2003, 2004; Lages, Lages, and Lages 2005; Lukas, Whitwell, and Doyle 2005).

We hypothesize that both the activities and the metrics aspects have separate but related effects on performance and CEO satisfaction. Because the activities aspect precedes the metrics aspect both theoretically and logically, we test the activities aspect first:

> H_3: The ability to measure performance across the range of marketing activities a firm employs positively influences firm performance.
>
> H_4: The ability to measure performance across the range of marketing activities a firm employs is positively associated with CEO satisfaction with marketing.

As we noted previously, the identification of metrics in use is one of the main streams of MPM research (e.g., Ambler, Kokkinaki, and Puntoni 2004; Barwise and Farley 2003, 2004; Lages, Lages, and Lages 2005; Lukas, Whitwell, and Doyle 2005). An assumption underlying this research stream is that choice of metrics matters. Researchers in this area have concluded that in their choice of metrics, firms should employ both financial and nonfinancial metrics (Clark 1999; Rust et al. 2004) and that they should compare these against goals and competitors (Ambler 2003). Thus, we expect that firms that follow this guidance and are able to assess marketing performance using a broad set of metrics (financial and nonfinancial, in relation to goals, and in relation to competitors) should outperform those that lack this ability. It has previously been noted that the academic community's focus on metrics in use has had little impact on practicing marketers (Clark 1999). Reflecting this, we are interested in isolating the impact of metrics ability on performance and CEO satisfaction beyond that which is accounted for by activities ability. Thus:

> H_5: The ability to provide a comprehensive set of metrics positively influences firm performance.
>
> H_6: The ability to provide a comprehensive set of metrics is positively associated with CEO satisfaction with marketing.

Dashboards are a variation of a balanced scorecard (Kaplan and Norton 1992) and are used as a means to report key metrics to senior management from the array of information generated by corporate information systems (Paine 2004; Wind 2005). Ambler (2003) describes a dashboard as a refined set of marketing performance data, usually presented together, which communicate an overview of strategic performance. Two important elements of dashboards are that they provide automated or (close to) real-time reporting (Iyer, Lee, and Venkatraman 2006; Wind 2005) and that they enable users to "drill down" to program-level details (Miller and Cioffi 2004). It has been noted that dashboards, which are increasingly popular among marketing practitioners, have received only limited attention in marketing research (Rogers 2003). Recently, Srivastava and Reibstein (2005) have called for more research on the role of dashboards in managing marketing productivity.

Dashboards are viewed as a means by which information can be summarized and readily communicated to senior decision makers (Srivastava and Reibstein 2005). It is argued that this distilling of data increases the perceived value and managerial use of information (Peyrot et al. 2002), which in turn creates a closer link between marketing activities and firm goals (McGovern et al. 2004; Miller and Cioffi 2004). Therefore, the use of a marketing dashboard is hypothesized to act as a moderator in the relationships between ability to measure and performance and between ability to measure and CEO satisfaction.

> H_7: The greater the use of a marketing dashboard, the more positively MPM will influence firm performance and CEO satisfaction.

The study controls for firm size and firm age because both variables have previously been shown to affect performance (e.g., Ahuja and Lampert 2001; Miles, Covin, and Heeley 2000). In controlling for firm age, the study follows previous research on high-tech firms (e.g., Hill and Naroff 1984). Firm age is accepted as influencing performance through the ability to learn in the customer relationship and on competitive advantage outcomes (Zahra, Ireland, and Hiltt 2000). We summarize the relationships outlined in this section in Figure 1.

Method

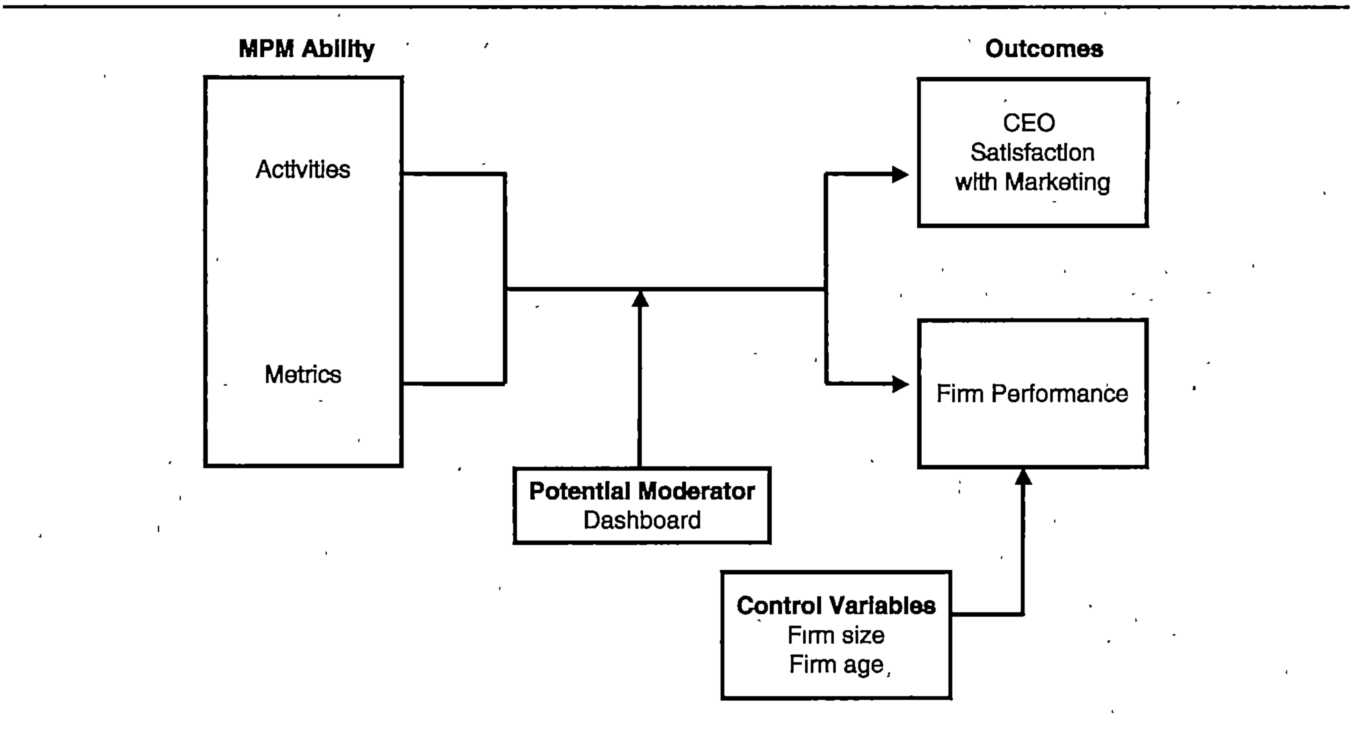
Sample and Procedure

A survey of senior marketers in high-tech firms about MPM ability, CEO satisfaction with marketing, and aspects of firm performance produced the primary data for our research. We used the membership list of the CMO Council as the sample frame for our study. The CMO Council is a U.S.-based, not-for-profit organization for senior marketers in high-tech firms. The council's membership is global, though at the time of study, it was heavily skewed toward North American firms. The membership list contains names and background information (title, firm, and contact details) for all members. We collected survey responses through an online, structured survey. We supplemented the primary data captured through the survey with secondary data on aspects of firm performance.

The study sought responses from key informants. Because the CMO Council's membership is limited to senior marketers, we included in the sample all members other than those who worked in marketing services providers, such as advertising agencies. We subsequently analyzed the responses to ensure that the respondents had senior marketing responsibilities (job title) before we included them in further analysis. The views of key informants are widely used within the marketing literature (see, e.g., Day and Nedungadi 1994; Moorman and Rust 1999; Narver and Slater 1990).

Before constructing the questionnaire, we conducted preliminary in-depth interviews with 17 chief marketing officers (CMOs). These discussions focused on the interviewees' understanding of and motivations for measuring marketing performance. A strong functional orientation was apparent; interviewees were most interested in measuring

FIGURE 1
Conceptual Model



the performance of the marketing function as opposed to the broader marketing performance of the firm. In addition, respondents were interested in assessing performance impact at the firm level. In short, MPM was viewed as an assessment of the marketing function's contribution to firm performance. The interviews provided a basis for the development of our survey questionnaire.

The questionnaire was divided into three sections that contained questions related to MPM ability, firm performance, and respondent profile. The questionnaire included a 15-item scale to quantify the ability to measure performance across a range of marketing activities and a 4-item scale to measure the ability to assess performance using a comprehensive set of metrics. These scales reflected the views captured from our interviews with CMOs and a review of the literature. To test for comprehension, relevance, and completeness, we pilot-tested the questionnaire with ten senior marketers from the CMO Council. Participants in the pilot phase were asked to identify any problems they encountered with the e-mail invitation, the content of the questionnaire, or the process of completing it online. Participants were also asked to evaluate the clarity of the questions and the response formats. No major difficulties were identified, though we clarified some of the response options and revised the questionnaire accordingly.

The survey was administered online between February and March 2004. A total of 810 marketers received e-mail notification of the survey. This was followed 14 days later by a reminder e-mail to nonrespondents. Each e-mail contained an embedded link to the survey. We received 214 usable response, for a response rate of 26.4%. This response rate was highly satisfactory given that rates ranging from 12% to 20% are considered acceptable for cross-sectional samples (Churchill 1991). We tested for nonresponse bias using time-trend analysis (Armstrong and Overton 1977). We selected two subsamples from early and late respondents. Because these did not differ in terms of respondent profile or the variables of interest, we concluded that nonresponse bias was not a significant concern.

We collected survey responses over a four-week period. After that time, we made the survey available through several additional channels, most notably a *BusinessWeek* research panel. This produced an additional 98 qualified respondents, for a total of 312 responses. Subsequent analysis of these additional 98 respondents indicated that they were not materially different from the first 214 respondents in terms of job title and sector. Furthermore, their responses to the key issues under consideration in the study were similar to those of the original 214 respondents. Consequently, we included them for further analysis. In total, we included 312 responses in subsequent analysis.

The job titles of respondents represented the range of possible senior marketer titles: 17% were CMOs, 40% were vice presidents of marketing, and 15% were marketing directors. Of the 27% who answered "other," most were senior managers with titles such as president or vice president of sales and marketing. Respondent firms were drawn from a cross-section of information technology–related sectors: 36% were software providers, 35% provided Internet-related services, 3% provided components, 3% provided computer systems, and 3% provided networking products and services. Peripherals and integration accounted for 2% and 1%, respectively. Of the 17% that responded "other," most were application service providers, information technology consulting services, or telecommunications-related products and services. Firm age varied greatly among respondents, and most (>90%) were headquartered in North America.

Measurement[1]

We calculated MPM ability as the simple average of a firm's scores on the activities and metrics scales. We assessed MPM ability using a 15-item scale based on our in-depth exploratory interviews with CMOs. We recorded responses on a seven-point scale anchored by "poor" and "excellent." These activities included above- and below-the-line promotional activities as well as marketing planning and customer relationship management. As we noted previously, because the issue being addressed is marketers' inability to account for marketing activities, our specific interest here is in marketing's *ability* to assess this relationship. Having an ability does not necessarily mean using it, but given the demands being placed on marketers in high-tech firms at the time of this study to account for their contribution more effectively, it seems highly unlikely that any MPM ability would have remained latent. Therefore, we assume that any firm in our sample that had an MPM ability was indeed using it. Discussions with the CMO Council's Steering Committee and interviews with 17 CMOs during the exploratory phase of our research indicated that this assumption was reasonable.

In our study, metrics is a construct that consists of the summed responses to four questions. Again, we captured responses on a seven-point scale anchored by "poor" and "excellent." Over the past 40 years, ranges of metrics have been proposed for MPM (for a review, see Clark 2001). These include both financial and nonfinancial measures. The inclusion of nonfinancial measures is considered an important progression because it helps provide a more complete description of marketing's contribution. Financial and nonfinancial measurement are two of the four aspects of metrics ability we considered. The other two aspects of metrics we assessed are related to benchmarking. Bonoma (1989) was one of the first researchers to argue for greater benchmarking of marketing performance. More recently, Vorhies and Morgan (2005) have demonstrated the impact of the benchmarking of marketing capabilities on firm performance. Consequently, we included the ability to benchmark against plan and against competitors in our understanding of metrics. The resultant scale was reliable (α = .83).

Dependent measures. Our dependent measures were firm performance and CEO satisfaction with marketing. We assessed firm performance using both primary and secondary data. Primary data were provided through our survey of senior marketers. In the past, the most common measures of output in firm-level marketing performance studies have been profit, sales, market share, and cash flow (Bonoma and Clark 1988). Financial measures, such as sales and profit, continue to be the most important MPMs (Clark 2000; Kokkinaki and Ambler 1999). Several studies have suggested that managers balance profitability and sales growth (McKee, Varadarajan, and Pride 1989; Slater and Narver 1996), and others have considered market share a measure of firm performance (Jaworski and Kohli 1993). Accordingly, and in line with previous studies, we measured performance as the mean of a respondent's rating for his or her firm's sales growth, market share, and profitability performance relative to all other competitors. We captured responses on a five-point scale anchored by "very poor" and "outstanding." We measured CEO satisfaction with marketing as the response to a single question. We captured responses on a five-point scale anchored by "excellent" and "poor."

Following the work of Rust, Moorman, and Dickson (2002), we captured secondary data on firm performance through two measures: return on assets (ROA) and stock returns. We calculated ROA as the firms' overall ROA for the 12 months subsequent to our original study, as reported in COMPUSTAT. This time lag enabled us to determine the direction of causality between MPM and firm performance.

Using data provided by the University of Chicago's Center for Research in Security Prices (CRSP), we measured stock returns as the firms' size-adjusted stock returns for the 12 months subsequent to the original study. The CRSP provides data on stocks traded on each of the major U.S. stock exchanges: NYSE, AMEX, and NASDAQ. We calculated returns as the difference between an individual firm's stock returns and the value-weighted average return for all firms in the same size decile of the sample firm in CRSP's size decile portfolio for each month. Return data were adjusted for both stock dividends and splits for each firm by CRSP (Rust, Lemon, and Zeithaml 2004). We calculated each firm's return for the period, referred to as the holding period return, as follows:

$$R_i = [(P_1 - P_0) + (D_1)/P_0)],$$

where R_i is the return on stock i, P_1 is share price in month 1, P_0 is share price in the previous month, and D_1 is the dividend associated with Month 1.

We determined the value-weighted portfolio return for each month from the CRSP portfolio assignment number. We calculated returns by compounding both the return for the firm and the value-weighted returns for the portfolio for the 12 months. This enabled us to determine the return as the difference between the compounded return for the firm and the compounded portfolio return.

The cumulative size-adjusted excess return then becomes the return on the stock less the return on the relevant CRSP market capitalization decile portfolio:

$$CAR_i = [\Sigma(R_{it} - R_{sizet})],$$

where R_{it} is the cumulative return on stock i over the 12 months and R_{sizet} is the matching return on the appropriate CRSP market capitalization decile portfolio.

Potential moderator. Responding to recent calls for a consideration of the role and impact of marketing dashboards, we included dashboards as a potential moderator. We assessed the use of a marketing dashboard as the mean of responses to three questions related to the existence of a dashboard and its functionality, which, as we noted previously, include automated updating and program-level drill-down capability ($\alpha = .88$).

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[1] Scale items for each of the MPM measures appear in the Appendix.

Control variables. We included two control variables that are commonly recognized in the marketing and strategy literature as influencing firm performance: firm size and firm age. We operationalized firm size as the firm's annual revenue. Previous research has suggested that number of employees, sales, and assets are all equally appropriate indicators of a firm's size (e.g., Harrison and Torres 1988). We measured firm age as the number of years the firm has been in business.[2]

Measurement properties. After data collection and before testing our hypotheses, we conducted several procedures to examine the psychometric properties of and to purify our measures. We judged the 15-item activities scale to have face validity because it reflects the primary activities of the marketing function as commonly outlined in the literature. To ensure content validity, senior marketers on the CMO Council's MPM Steering Committee provided expert screening of scale items (Churchill 1979; Malhotra 1996). Exploratory factor analysis indicated that the scale comprised four factors. The first factor accounted for 36% of the total variation in the scale, the second factor accounted for 11% of the variation, and the third and fourth factors each accounted for 7% of the variation. Thus, the third and fourth factors explained little more than any one of the individual items. To isolate key factors further, we subjected the data to Varimax rotation. We set a factor loading of .4 as the cutoff to establish themes and labels for the factors. This is consistent with previous studies (e.g., Mitchell and Walsh 2004; Washburn and Plank 2002). In deciding which items to use to compute a "factor score," we also applied Bedford's criterion of a primary loading being at least .2 greater than any cross-loading in addition to the .4 criterion. The latter criteria resulted in the loss of three items. Consistent with Gerbing and Anderson's (1988) recommendations, we used confirmatory factor analysis to evaluate and refine the resultant scales further. We conducted the factor analysis using the 12 items remaining at the end of the exploratory factor analysis. As part of this analysis, it was specified that four factors should be extracted rather than allowing for an unforced selection of factors. The resultant four factors explained 65% of the total variance. Varimax rotation identified the same factor structure (see Table 1) as that which we determined on the basis of the exploratory analysis.

The four factors are labeled as follows:

- Direct: the ability to measure below-the-line and online marketing activities (three items).
- MGT: the ability to measure performance of management and analysis activities (four items).
- PR: the ability to measure public relations, analyst, and other stakeholder relations activities (three items).
- Brand: the ability to measure performance of branding and advertising activities (two items).

Our next step was to examine the discriminant validity of our measures. Table 2, Panel A, presents the descriptive statistics and correlation matrix for the variable set. Alpha coefficients for all measures were greater than .7, indicating that reliability is acceptable (Nunnally and Bernstein 1994). As we expected, activities and metrics, the two aspects of MPM in our conceptual model, were highly correlated, as were the dashboard and metrics measures. Notably, CEO satisfaction with marketing was minimally correlated with overall firm performance, with a correlation coefficient of .13.

The results of the tests for discriminant validity appear in Table 2, Panel B. For each construct, average variance extracted (AVE) exceeds the .5 level that Hair and colleagues (1998) recommend. In addition, the AVE for each construct is higher than the squared correlation between that construct and any other construct, indicating that discriminant validity is not a problem (Fornell and Larcker 1981).

TABLE 1
Factor Matrix of MPM Activities

	Factor 1 (Direct)	Factor 2 (MGT)	Factor 3 (PR)	Factor 4 (Brand)
Branding				.79
Advertising				.805
Direct mail/e-mail campaigns	.810			
Telemarketing and contact management	.804			
Web site and Internet presence	.621			
Trade shows and events			.641	
Public relations and internal communications			.797	
Analyst and stakeholder relations			.670	
Channel marketing		.693		
Customer relationship management systems		.729		
Market research		.690		
Budgeting		.595		

Notes: All but the highest loadings are suppressed.

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[2] When analyzing the impact of MPM on the ROA and stock returns of public companies, we extracted size from COMPUSTAT and age from company reports.

Analysis and Results

Firm Performance: Primary Data

In H_1 and H_2, we predicted that there would be a positive relationship between MPM ability and both firm performance and CEO satisfaction with marketing. We tested these hypotheses using hierarchical moderated regression models (Schoonhoven 1981). Reflecting our conceptual model and to test H_7, we considered marketing dashboards a potential moderator of the relationship between MPM and each of the dependent variables. We specified two equations, one for each dependent variable. We entered data into the equations in two steps. The first step contained the main effects associated with MPM and the potential moderator. In addition, in testing the relationship to firm performance, we entered the two control variables at this time. The second step contained the interactions defined by mean centering the main effects and creating products of dashboard and MPM. Mean centering enabled us to control for the effect of multicoliniarity, as Aiken and West (1993) and Cohen and colleagues (2002) recommend. The introduction of the interaction term failed to produce a significant effect on either firm performance or CEO satisfaction with marketing. For performance, change in $F(1, 283) = 1.206$, $p = .273$. For CEO satisfaction with marketing, change in $F(2, 290) = .558$, $p = .298$. Given these results, we reestimated the model including MPM and, in the case of firm performance, the two control variables. The results appear in Table 3.

TABLE 2
Summary Statistics, Correlation Matrix, and Discriminant Validity

A: Summary Statistics and Correlation Matrix

	M	SD	Items	1	2	3	4	5	6	7	8	9
1. Activities	4.1	.97	4	*.72*								
2. Metrics	3.64	1.44	4	.71	*.83*							
3. Dashboard	3.17	1.74	3	.56	.68	*.88*						
4. Firm size	32.06	71.12	1	–.01	–.03	.05	—					
5. Firm age	23.58	23.79	1	.09	.12	–.010	.39	—				
6. CEO satisfaction	3.48	.93	1	.53	.44	.35	.06	–.04	—			
7. Performance	5.02	1.32	3	.27	.23	.27	–.05	.0	.34	*.84*		
8. ROA	5.79	12.67	1	.31	.24	.18	.06	.07	.23	.44	—	
9. Stock returns	–.1	.25	1	.17	.2	.0	–.02	.05	.1	.09	.12	—

B: Discriminant Validity

		Squared Correlations			
	AVE	1	2	3	4
1. Activities	.56				
2. Metrics	.67	.50			
3. Dashboard	.80	.31	.46		
4. Performance	.80	.07	.05	.07	

Notes: Alphas for multi-item measures are in italics on the diagonal in the correlation matrix.

TABLE 3
The Impact of MPM on Firm Performance and CEO Satisfaction: Primary Data

	Firm Performance		CEO Satisfaction	
Model Statistics				
Adjusted R^2	.148		.220	
F statistic	16.566		84.219	
d.f.	3, 285		1, 294	
p value	<.001		<.001	
Final Predictors	b^a	t^b	b^a	t^b
MPM	.253	4.608*	.472	9.177*
Firm size^c	.320	4.722*		
Firm age^c	–.136	–2.015		

*$p < .001$.
[a] Standardized coefficients
[b] t refers to the t-statistic for the estimated coefficients.
[c] We do not include firm size and firm age as control variables when considering the impact of MPM ability on CEO satisfaction with marketing, because there is no basis in theory that would lead us to expect that these two variables affect the dependent variable.

The regression coefficients indicate that as we hypothesized, MPM ability is significantly associated with both firm performance and CEO satisfaction with marketing. These are the two hypothesized outcomes of MPM, and therefore the primary data support H_1 and H_2.

Next, we tested H_3–H_6, which predict that the two aspects of MPM, activities and metrics, each affect firm performance and CEO satisfaction with marketing. Again, we examined the interaction effects of activities with dashboard and of metrics with dashboard to determine whether either explained a significant level of variance when included in the linear regression model. Table 4, Panel A, provides the results of this analysis. Because entry of the interaction effects did not explain a significant level of variance (for firm performance, change in $F(2, 281) = .629$, $p = .534$; for CEO satisfaction with marketing, change in $F(2, 290) = .558$, $p = .573$), we report a model that contains the predictor variables only.

Again, we used hierarchical regression to test the relationship between the predictor variables and the dependent variables. Because our aim was to isolate the impact of metrics beyond the impact of activities, we entered the data in three steps. First, we entered the control variables. Second, we entered activities and considered the extent to which this explained a significant amount of variance. Third, we entered metrics to examine the degree to which it explained variance beyond that accounted for by activities.

Activities have a positive impact on firm performance and CEO satisfaction with marketing, and therefore H_3 and H_4 are supported in our analysis of the primary data. However, because the entry of metrics into the equation has a significant impact on CEO satisfaction with marketing but not on performance, the primary data reject H_5 but support H_6.

In our previous analysis of measurement properties, we explored the multidimensional nature of activities. To

TABLE 4
The Impact of Activities and Metrics on Firm Performance and CEO Satisfaction

A: Activities and Metrics

	Firm Performance		CEO Satisfaction	
Model Statistics				
Adjusted R^2	.134		.235	
F statistic	15.846		46.331	
d.f.	3, 285		2, 293	
p value	<.001		<.001	
Final Predictors	b[a]	t[b]	b[a]	t[b]
Activities	.243	4.389***	.380	5.296***
Metrics			.142	1.977*
Firm size[c]	.315	4.630***		
Firm age[c]	–.135	–2.003*		

B: Activities Factors

	Firm Performance		CEO Satisfaction	
Model Statistics				
R^2	.145		.219	
F statistic	13.150		28.56	
d.f.	4, 283		3, 291	
p value	<.001		<.001	
Final Predictors	b[a]	t[b]	b[a]	t[b]
Direct				
MGT			.235	3.568***
PR	.147	2.389*		
Brand			.164	2.679**
Metrics	.167	2.672	.178	2.516*
Firm size	.320	4.720***		
Firm age	–.123	–1.820		

*$p < .05$.
**$p <$ 01.
***$p < .001$.
[a] Standardized coefficients.
[b] t refers to the t-statistic for the estimated coefficients.
[c] We do not include firm size and firm age as control variables when considering the impact of MPM ability on CEO satisfaction with marketing, because there is no firm basis in theory that would lead us to expect that these two variables affect the dependent variable.

examine the impact of the activities factors further, we calculated the regression coefficients for each factor on each dependent variable. The results of this analysis appear in Table 4, Panel B. Because interaction effects were not significant, the table reports the main effects of the four activities factors, metrics, and the control variables. Again, we conducted a three-step hierarchical regression. For firm performance, the entry of the PR factor into the model with firm size and firm age explained a significant level of additional variance in firm performance (change in F(1, 284) = 15.832, $p < .001$). The subsequent entry of metrics into this model in the third step also explained a significant level of additional variance in firm performance (change in F(1, 283) = 7.139, $p = .008$).

For CEO satisfaction, the entry of the MGT and Brand factors into the model with firm size and firm age explained significant levels of additional variance (with MGT: change in F(1, 293) = 59.783, $p < .001$; with Brand: change in F(1, 292) = 15.233, $p < .001$). The subsequent entry of metrics into this model in the third step again explained a significant level of additional variance (change in F(1, 291) = 6.329, $p = .012$). The limited impact of individual factors suggests that a focus on individual dimensions is unwarranted and that a consideration of the full spectrum of activities provides a greater impact. The emergence of metrics as a significant predicator may be explained by the reduction of the explanatory power of the activities variable through disaggregation into its four factors.

Firm Performance: Secondary Data

In addition to collecting subjective measures of firm performance from key informants, we also collected objective performance data. We collected data on firm profitability and stock returns for the 12 months subsequent to the original study. This enabled us to counterbalance the problems that arise in interpreting causality solely on the basis of evidence from cross-sectional correlational studies. Our objective measures were ROA and size-adjusted stock returns. We collected these from the COMPUSTAT and CRSP databases, respectively. Because both databases are confined to publicly quoted firms, our sample size was necessarily reduced for this phase of the analysis (94 for ROA and 82 for stock returns compared with 312 for the primary analysis).

This phase of the analysis followed the same process as that for the primary data. First, we considered the potential moderating impact of dashboards on the relationship between MPM ability and performance through a two-step hierarchical moderated regression model. For both measures of performance, the entry of the interaction effects failed to generate a significant level of variance. For ROA, change in F(1, 80) = .068, $p = .794$. For stock returns, change in F(1, 74) = .292, $p = .591$. Reflecting this, the results in Table 5 present a model that contains MPM ability and the control variables. Because MPM ability has a significant impact on both ROA and stock returns, H_1 is supported. This is consistent with findings from our analysis of the primary data.

Second, we examined the relationship between both ROA and stock returns and the two components of MPM ability: activities and metrics. We followed the same procedure as that in the examination of primary performance data. We considered the interaction effects of activities with dashboard and of metrics with dashboard. The entry of the interaction effects did not explain a significant level of additional variance for either ROA (change in F(2, 80) = .031, $p = .969$) or stock returns (change in F(2, 71) = .377, $p = .688$). Because neither interaction effect explained significant additional variance, we report only the main effects in Table 6, Panel A.

As we discussed previously, activities and metrics are conceptually related, and to reflect this, we carried out a three-step hierarchical regression analysis. We entered firm size and firm age into the model in the first step. In the second step, we entered activities. Finally, in the third step, we entered metrics to examine whether further variance was explained. Activities have a positive impact on ROA, but the results are not significant for stock returns. This finding provides partial support for H_3. Consistent with our analysis

TABLE 5
The Impact of MPM on Firm Performance: Secondary Data

	ROA		Stock Returns	
Model Statistics				
Adjusted R^2	.70		.024	
F statistic	3.119		1.651	
d.f.	3, 82		3, 76	
p value	.030		.185	
Final Predictors	b[a]	t[b]	b[a]	t[b]
MPM	.289	2.704**	.187	1.658*
Firm size	.073	.692	–.019	–.171
Firm age	.084	.788	.134	1.189

*$p < .05$.
**$p < .01$.
[a]Standardized coefficients.
[b]t refers to the t-statistic for the estimated coefficients.

TABLE 6
The Impact of Activities and Metrics on Firm Performance: Secondary Data

A: Activities and Metrics

	ROA		Stock Returns	
Model Statistics				
Adjusted R^2	.173		.004	
F statistic	7.078		1.117	
d.f.	3, 84		3, 75	
p value	<.001		.348	
Final Predictors	b^a	t^b	b^a	t^b
Activities	.230	2.264*	.115	.959
Metrics				
Firm size	.409	3.241**	.023	.162
Firm age	–.167	–1.347	.132	.940

B: Activities Factors

	ROA		Stock Returns	
Model Statistics				
R^2	.184		.047	
F statistic	7.528		2.295	
d.f.	3, 84		3, 75	
p value	<.001		.085	
Final Predictors	b^a	t^b	b^a	t^b
Direct				
MGT	.243	2.504*		
PR				
Brand				
Metrics			.236	2.084*
Firm size	.459	3.734***	.003	.019
Firm age	–.151	–1.233	.141	1.027

*$p < .05$.
**$p < .01$
***$p < .001$.
[a] Standardized coefficients.
[b] t refers to the t-statistic for the estimated coefficients.

of the primary data, dashboards do not have a significant moderating effect. Consequently, we find no support for H_7.

In analyzing the impact of the activities factors, we began by considering the potential moderating influence of dashboards. Because the interaction effect was not significant, we did not include it in further analysis. Table 6, Panel B, summarizes the main effects of activities. The entry of MGT into the model with firm size and firm age explained a significant level of additional variance in ROA (change in $F(1, 84) = 6.268$, $p = .014$). None of the four factors or metrics had a significant impact on stock returns, but the entry of metrics into the model with firm size and firm age explained a significant level of additional variance (change in $F(1, 75) = 4.344$; $p = .041$). Again, the limited impact of individual factors indicates that consideration of the full set of activities may offer the greatest benefit as a driver of firm performance.

Discussion

Summary of Findings

Taken together, our analysis of the primary and secondary data indicates that MPM ability has a positive impact on firm performance in the high-tech sector. We found that firms with a strong MPM ability tend to outperform their competitors, as reported by senior marketers. In addition, the results suggest that MPM ability has a positive influence on ROA and on stock returns. These findings are important given the centrality of performance outcomes to current academic and managerial interest in the MPM. We summarize the findings in Table 7.

In addition, we found that MPM ability has a significant, positive impact on CEO satisfaction with marketing. Because increasing marketing's stature at the board level is

TABLE 7
Summary of Hypothesized Results

	Performance		CEO Satisfaction		ROA		Stock Returns	
MPM Activities	**Hypothesis**	**Supported**	**Hypothesis**	**Supported**	**Hypothesis**	**Supported**	**Hypothesis**	**Supported**
MPM	+	Yes	+	Yes	+	Yes	+	Yes
Activities	+	Yes	+	Yes	+	Yes	+	No
Metrics	+	No	+	Yes	+	No	+	No
MPM × dashboard	+	No	+	No	+	No	+	No
Activities × dashboard	+	No	+	No	+	No	+	No
Metrics × dashboard	+	No	+	No	+	No	+	No

Notes: + = a positive hypothesized relationship. Yes = the hypothesis was supported. No = the hypothesis was not supported.

a focus of attention for both academic and practitioner communities, this is an important finding. Although the argument linking marketing accountability and marketing's influence is regularly posited, this is the first study to demonstrate this relationship successfully. Our demonstration of the link between MPM ability and CEO satisfaction with marketing lends support to researchers, such as Webster, Malter, and Ganesan (2005), who have called for greater accountability in marketing. Our findings also support the Marketing Science Institute's (2004) ongoing prioritization of performance measurement as a means of raising the profile of the discipline.

Marketing performance dashboards have captured the attention of practitioners and, more recently, marketing academics. However, we did not find that the existence of dashboards influenced the key relationships under consideration in our study.

We find that activities ability has four dimensions related to direct marketing, management, public relations, and brand. The impact of these factors varies across the dependent variables we considered. Notably, the ability to measure brand and management activities influences CEO satisfaction with marketing.

After we account for activities, the second component of MPM ability, metrics, does not have a significant additional impact on firm performance. However, it significantly affects CEO satisfaction with marketing.

Implications for Managers

The results of this study have several important managerial implications. Development of MPM ability requires that marketers divert part of their budget and attention away from actual marketing programs and toward measurement efforts; this would be counterproductive if it did not improve performance. Our study provides support for just such a diversion of resources, indicating that it can positively affect both firm performance and marketing's stature within the organization, at least for firms that operate in the high-tech sector.

Given that MPM ability offers demonstrable benefits, the question arises as to what should be measured and how. Although this study clearly identifies four factors that make up the activities aspect of performance measurement ability (direct marketing, public relations, brand, and management), it is noteworthy that each factor alone has relatively weak relationships to firm performance and CEO satisfaction with marketing. This implies that efforts to drive improvement in ability to measure a single marketing activity, no matter how important the activity is to the firm, are less valuable than a comprehensive effort to develop the ability to measure performance across the entire range of marketing activities employed.

In addition, our findings suggest that the ability to use a comprehensive set of metrics is associated with higher CEO satisfaction with marketing. In this respect, developing the ability to measure performance with a combination of financial and nonfinancial indicators that allow for a comparison of performance against plans and against competitors would seem to be beneficial for marketers. However, although a large part of the MPM literature has focused on which metrics are being or should be used, this study finds no separate impact on firm performance attributable to the ability to use a range of metrics.

Finally, our study questions the merit of the current high level of practitioner enthusiasm for marketing performance dashboards. Such dashboards have been presented as a means to present and communicate performance data more effectively. However, we do not observe any moderating effect of dashboards on the relationship between MPM and firm performance or CEO satisfaction with marketing. Because this is one of the first studies to explore the impact of performance dashboards in marketing and given that their adoption and functionality continue to evolve, our findings are not definitive; researchers and managers alike need to continue to explore this emerging area.

Limitations and Further Research

The membership list of the CMO Council, which we used as the sample frame for our study, is not a complete list of senior marketers in high-tech firms globally or even in North America, and therefore the results of this study cannot be generalized to the whole population of senior technology marketers. However, although we recognize the sample frame as being incomplete, we deemed access to the membership of the organization and the expected response rate to be sufficient to justify its use. It would be useful to replicate the research using a more complete sample frame. Furthermore, it would be useful to extend the research to other sectors because though pressure to demonstrate marketing's contribution is strongly evident in high-tech firms, this pressure is also evident in many other industries. Given the global nature of MPM research (e.g., Barwise and Farley 2004), it would also be useful to replicate this study with samples from outside the United States.

The research relies on the views of a single key informant (the senior marketer) in each firm. Although the key informant approach is common, the use of multiple informants from a single firm may allow for a more rounded perspective. In addition, as we noted previously, the absence of any evidence of the effect of dashboards might be due to the way we conceptualized them in this study; therefore, alternative conceptualizations are worth exploring. Similarly, although we found strong evidence of the impact of MPM ability on CEO satisfaction with marketing, we assessed the latter through a single-item measure. Future studies could pursue a more comprehensive consideration of marketing's stature within the firm.

An assumption underpinning this research is that firms with the ability to measure performance do so. We have already outlined the rationale for this assumption. However, notwithstanding the intense pressure on marketers to account for the performance impact of their activities, it is possible that a nontrivial portion of this ability remains latent in some firms. Accordingly, assessing actual MPM in future research would be useful.

Finally, although the focus of this study was on the relationship between MPM ability and firm performance and CEO satisfaction with marketing, it is possible that there are important mediating variables that could also be considered.

As we noted previously, it has been posited that improved learning may be a route through which MPM ability is positively related to improved performance, and as such, further research that incorporates this potentially mediating variable would be worthwhile. In addition, although we expect that measurement ability leads to improved marketing, we do not control for actual marketing performance in this study.

Appendix
Measures

MPM Ability

MPM ability. For each of the following marketing activities, please rate your company's ability to measure performance (1 = "poor," and 7 = "excellent").

- •Marketing planning
- •Branding
- •Advertising
- •Direct mail/e-mail campaigns
- •Telemarketing and contact management
- •Web site and Internet presence
- •Tradeshows and events
- •Promotions
- •Sales and marketing collateral
- •Public relations and internal communications
- •Analyst and stakeholder relationships
- •Channel marketing
- •Customer relationship management systems
- •Market research
- •Budgeting

Ability to generate a comprehensive set of marketing metrics. Please rate your company's current ability to provide the following MPM information (1 = "poor," and 7 = "excellent").

- •Financial indicators of marketing performance
- •Nonfinancial indicators of marketing performance
- •Benchmark indicators of marketing performance against plans
- •Benchmark indicators of marketing performance against competitors

Outcomes

Primary firm performance outcomes. Please indicate your firm's performance over the last year relative to all other competitors in the primary market that you serve (1 = "very poor," and 7 = "outstanding").

- •Sales growth
- •Market share
- •Profitability

Secondary firm performance outcomes.

- •ROA (COMPUSTAT)
- •Size-adjusted stock returns (CRSP)

CEO satisfaction with marketing. In your opinion, what is your CEO's evaluation of your company's current marketing performance?

- •Excellent
- •Above average
- •Average
- •Below average
- •Poor

Potential Moderator

Use of a marketing dashboard. Please rate your company's current ability to provide the following MPM information (1 = "poor," and 7 = "excellent").

- •High-level "dashboard" of key marketing performance indicators
- •Automated reporting of performance from the full range of marketing activities
- •Automated "drill-down" information for detailed analysis of individual marketing programs

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Rex Yuxing Du, Wagner A. Kamakura, & Carl F. Mela

Size and Share of Customer Wallet

Many companies collect substantial information about their interactions with their customers. Yet information about their customers' transactions with competing firms is often sparse or nonexistent. As a result, firms are often compelled to manage customer relationships from an inward view of their customers. However, the empirical analysis in this study indicates that (1) the volume of customers' transactions within a firm has little correlation with the volume of their transactions with the firm's competitors and (2) a small percentage of customers account for a large portion of all the external transactions, suggesting the considerable potential to increase sales if these customers can be correctly identified and incentivized to switch. Thus, the authors argue for a more outward view in customer relationship management and develop a list augmentation–based approach to augment firms' internal records with insights into their customers' relationships with competing firms, including the size of each customer's wallet and the firm's share of it.

With continued advances in information technology, firms are capturing an expanding array of detailed records of their interactions with their individual customers. Such information has been used to generate not only behavioral insights but also important metrics, such as customer lifetime value and customer equity, and it is becoming indispensable in guiding firms' customer relationship management (CRM) initiatives (Rust, Zeithaml, and Lemon 2000). Yet this abundance of internal (within the firm) information is often accompanied by a dearth of information on external (outside the firm) customer activities. As a result, firms are often compelled to manage customer relationships using a view of their customers that is based mostly on internal records. However, such an inward focus could provide misleading measures of a customer's market potential. For example, customers who appear to have high value based on internal records may have modest growth potential if they have only limited requirements that are served by competing firms. In contrast, customers who have a high transactional volume with competing firms may be good targets for growth to the extent that a firm can attract a larger share of their business. Bell and colleagues (2002) indicate that this lack of individual-level, industrywide consumer data is a primary barrier to CRM. In the absence of such information, it may be difficult for customer loyalty programs, cross- and up-selling applications, targeted promotions, and many other marketing efforts to achieve the best return on investment.

Our study attempts to redress this limitation by developing an approach to determine how much business a customer transacts with a focal firm's competitors or, in industry parlance, to estimate the focal firm's share of the customer's total wallet. Such an approach could prove useful in CRM. For example, without information pertaining to a customer's demand from competing firms, firms cannot discern a customer with high firm share and small total wallet from a customer with low firm share and large total wallet. Yet the marketing prescriptions for each differ considerably. For the former customer, the marketing prescription might be to generate new primary demands (if possible), and for the latter customer, it might be more appropriate to encourage switching to the firm's existing products.

Overview of Our Approach

A way to address the problem of not knowing how much business a customer does with the competition is through a procedure commonly known as "list augmentation" or "database augmentation," which overlays data obtained from customer surveys or secondary sources with existing databases (e.g., Crosby, Johnson, and Quinn 2002; Kamakura and Wedel 2003; Kamakura et al. 2003; Wyner 2001). A typical list augmentation exercise involves the following steps: First, the focal firm (often anonymously) surveys a random sample of its customers, collecting information that is not available from the firm's internal database. Second, the information from the survey is linked to information already stored in the internal database (e.g., transaction history, demographics) to form a sample with a complete set of records. Third, from this sample, predictive models that leverage the correlation patterns between the survey results and the internal data can be developed. Finally, the best-performing model is applied to the remainder of the customer database to produce individual-level estimates of the survey results. Compared with the costs of developing and maintaining the customer database, the costs of implementing list augmentation are fairly small.

Central to this general framework is the development of an effective predictive model. In this study, by augmenting the firm's internal database with survey information on a

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sample of customers' purchases from the firm's competitors, we present three models for estimating a customer's total purchases in a category and how large a share of these purchases comes from the focal firm. To our knowledge, this is the first study in the marketing literature to use list augmentation to impute wallet size and share of wallet.

We apply our models to a proprietary data set provided by a major U.S. bank. The data set contains information for more than 34,000 customers on their uses of ten categories of financial products that both the bank and its competitors offer. We first calibrate the models on a subsample with information on account balances both inside and outside the bank. We then use the calibrated models to predict total and share of requirements in each category for a validation sample using only inside balances (the outside balances provide the basis for validation), thus emulating the application of the models to the rest of the customer database, in which information about outside balances is unavailable.

Key Findings

One of our three models stands out in terms of its predictive performance and managerial interpretability. It correctly predicts 72% of the time whether a customer uses a product offered by the focal bank's competitors, and it offers the most accurate estimates of total and share of category requirements. Furthermore, it yields insights into customers' share decisions that can be used in guiding future CRM initiatives. We highlight several findings, some of which we conjecture may be idiosyncratic to the bank under study (e.g., Finding 3), whereas others may be generalizable across firms and industries (e.g., Findings 1, 2, and 4).

1. Longer relationships are not necessarily associated with larger share of wallet; the correlation between customer tenure and share of requirements is neutral or negative in four of the ten categories we analyze. This is consistent with the argument that relationship duration and customer share should be considered two separate dimensions of customer relationship (Reinartz and Kumar 2003).
2. Customers with high share in one category also tend to have high share in another category, indicating that customers' share decisions are positively correlated and, thus, the potential for positive externalities across categories.
3. Customers' share and total purchase decisions are sometimes negatively correlated, suggesting that for some categories, customers with small shares within the focal firm tend to transact a large volume outside it. These customers might represent significant opportunities for volume growth to the extent that the focal firm can induce them to switch.
4. Customers with higher incomes tend to balance share of requirements across firms. This may suggest either that the focal firm is not serving such customers well or that customers with higher incomes have incentives to allocate business across firms.

To investigate the managerial value of our proposed approach further, we conduct a series of targeting simulations and find that substantial lifts in targeting efficiency can be obtained by using estimated total and share of wallet. For example, 13% of customers in the validation sample are identified as high-potential customers because their estimated total wallet is in the top quintile and their estimated share of wallet at the focal firm is below average. These customers account for 53% of the validation sample's financial requirements that are fulfilled outside the focal bank, suggesting considerable potential for increasing revenue to the extent that the focal firm can induce them to switch.

We proceed as follows: The next section discusses in more detail the value of share of category requirements in managing relationships with individual customers. We then present the three models for estimating total and share of category requirements. This is followed by our empirical illustration, in which we present the managerial problem and data, the models' predictive performances and parameter estimates, and the results from several customer-targeting simulations. Finally, we summarize and discuss directions for further research.

Share of Category Requirements as an Outward-Looking Relationship Metric

Customer relationship management efforts are often targeted toward a firm's best customers, defined as those who contribute the most to the firm's bottom line. Such strategies are effective when firms want to strengthen relationships with "high-value" customers and mitigate the likelihood that these customers will defect to competing firms. However, it could be myopic to target such customers for relationship development because profitability measures are blind to the relationships a customer might maintain with competitors, and there may be little correlation between the customer's growth potential and his or her current or prior net contributions. Such low correlation may predominate in industries in which customers maintain concurrent relationships with multiple providers. Yet the volume of a customer's business with the competition represents an important source of his or her potential profitability. Indeed, several researchers have proposed or shown the link between customer share and profitability. For example, Garland (2004) examines the role of share of wallet in predicting customer profitability, finding that it is the single relationship-based measure with the most impact on customer contribution. Bowman and Narayandas (2004) and Keiningham, Perkins-Munn, and colleagues (2005) propose that share of wallet mediates the relationship between satisfaction and profits, an effect that Bowman and Narayandas (2004) empirically confirm. Reinartz, Thomas, and Kumar (2005) find that share of wallet positively affects customer tenure and profitability. Zeithaml (2000) proposes a conceptual model in which increased share of wallet is one of four factors that mediate the effect of customer retention on firm profits.

Because scant empirical evidence exists regarding the degree to which a customer's purchases inside and outside a firm correlate, we exemplify this issue using information we obtained from a large sample of customers of a major U.S. bank. For this sample, the bank knows each customer's financial portfolio with both the bank and its competitors. We find that 81% of the sample's internal assets (i.e., the sum of financial assets the sample customers have deposited in the bank) come from customers who are the top 20% in terms of internal asset (this is also known as the

"80/20" rule). Yet these same customers account for only 34% of the sample's external assets (i.e., the sum of financial assets the sample customers have deposited with the bank's competitors). Moreover, the bank's high-volume customers are often not the customers with the greatest growth potential; the correlation between internal assets and external assets is only .13. The pattern is more striking for debt products (e.g., credit card, personal loan, mortgage); 96% of the sample's debts with the focal bank come from customers who are the bank's top 20% clientele in terms of internal debt; however, these customers account for only 20% of the sample's external debts. The correlation between internal debts and external debts is –.04. In short, we find little correlation between a customer's internal and external requirements. Thus, any targeted CRM efforts predicated solely on internal information would miss many high-potential customers who have large sums of assets and debts outside the bank. This suggests that it is especially desirable to consider the bank's share of a customer's total wallet in gauging the customer's potential for growth.

Share of Category Requirements and Share of Wallet

To elaborate on the notion of customer share, we distinguish between share of category requirements and share of wallet. We define share of category requirements as the ratio of (1) a customer's requirements for a particular category of products from a focal supplier to (2) the customer's total requirements for products from all suppliers in the category (i.e., total category requirements). For a firm that offers multiple categories of products to its customers, we define the firm's share of wallet of a customer as the share of total requirements across all the product categories the focal firm offers. Thus, we define share of category requirements at the category level and share of wallet as an aggregate measure across all the categories in which the focal firm competes. We use share of category requirements because of its long-standing status in the literature and share of wallet because of its popularity among practitioners.

Share of category requirements has long been used as a metric of brand loyalty in the context of consumer packaged goods (Fader and Schmittlein 1993), and it is becoming an important metric of customer relationship strength under different names, depending on the industry that is using it (Malthouse and Wang 1998). For example, financial services companies call it "share of wallet," the automobile industry calls it "share of garage," the fashion industry calls it "share of closet," and the media industry calls it "share of eyeballs." Several articles in marketing have studied factors that can affect customer share. For example, Bhattacharya and colleagues (1996) explore the relationship between marketing-mix variables and brand-level share of category requirements. Bowman and Narayandas (2001) assess the impact of customer-initiated contacts on share of category requirements. Keiningham, Perkins-Munn, and Evans (2003) analyze the impact of customer satisfaction on share of wallet in a business-to-business environment. Verhoef (2003) investigates the differential effects of relationship perceptions and marketing instruments on customer retention and customer share. In the financial services area, researchers have examined the relationship between customer characteristics and share of wallet; for example, Baumann, Burton, and Elliott (2005) use survey data to identify customer characteristics that are associated with high share of wallet in retail banking, and Garland and Gendall (2004) use share of wallet as a factor in predicting customer behavior.

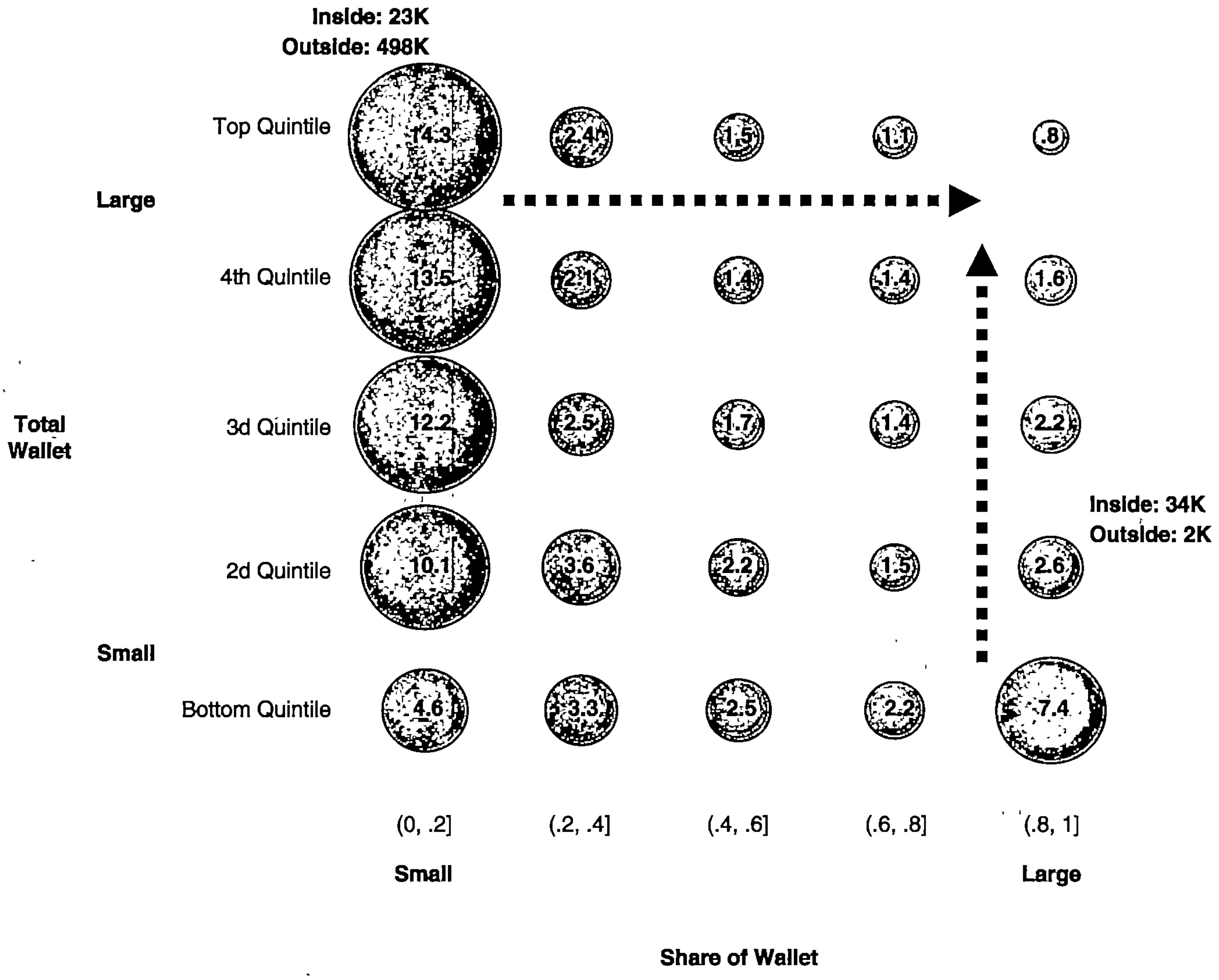
Share of Category Requirements as a Basis for Customer Segmentation

Several researchers have proposed the use of share of wallet as a basis for segmentation. For example, Anderson and Narus (2003) propose a framework for strategically pursuing a customer's business by selecting those with significant incremental share available and superior projected growth in need. Beaujean, Cremers, and Pereira (2005) propose the use of loyalty and share of wallet as bases for customer segmentation. Similarly, Reinartz and Kumar (2003) propose segmenting customers on the basis of customer tenure and share of wallet, and Keiningham, Vavra, and colleagues (2005) propose the combination of share of wallet and customer lifetime value for the same purpose. Although this work is largely theoretical, subsequently, we demonstrate empirically how share of wallet as a segmentation basis can yield actionable strategic insights.

By combining customers' share of wallet with their total wallet and using the bank data (which we describe in more detail subsequently), Figure 1 depicts a 5 × 5 segmentation scheme that offers an outward-looking view of the bank's customer base. The first dimension represents the focal bank's share of a customer's total financial needs (i.e., assets plus debts) divided into the following brackets: (0, 20%], (20%, 40%], (40%, 60%], (60%, 80], and (80%, 100%]. The second dimension is the customer's total financial needs by quintiles. The size of each circle in the figure indicates the percentage of customers who fall into the corresponding segment. Under this scheme, customers in different segments can be viewed as a portfolio of assets with different growth prospects.

Customers in the upper-right-hand corner of Figure 1 are "ideal" from the bank's perspective because they have large requirements for financial products and fulfill most of those requirements with the bank's offerings. However, these customers represent a small fraction of the bank's customer base, as is indicated by the size of their circles. Two growth strategies are indicated: The first is to migrate customers in the upper-left-hand corner toward the right (i.e., gaining a larger share of their business), and the second is to migrate those in the lower-right-hand corner upward (i.e., increasing their category requirements). We conjecture that the former strategy might prove more fruitful in the short run because a customer's category requirements are largely driven by his or her intrinsic needs and are constrained by financial resources. In our data, the two largest cells in the upper-left-hand corner of Figure 1 account for 28% of customers. In terms of short-term growth potential in assets and debts, customers in these cells account for 72%. Thus, we contend that customers in the upper-left-hand corner (i.e., those with a small share of wallet but a large total wal-

FIGURE 1
Segmentation Based on Share of Wallet and Total Wallet



let) could be the best prospects for marketers seeking near-term growth.

Unfortunately, it is difficult to implement such an outward-looking segmentation and targeting strategy in practice because firms rarely have accurate customer-level measures for share of wallet and total wallet. Without such information, customer segments in the upper-left-hand corner of Figure 1 are indistinguishable from those in the lower right by just looking at requirements fulfilled inside the focal firm. The main purpose of our study is to propose an approach that helps firms estimate these two important measures for their customers.

Share of Category Requirements as a Detector for "Silent Attrition"

Aside from being a segmentation basis, share of wallet can be viewed as an indicator of relationship strength, which can be used in early detection of customer attrition. Whereas customers who close accounts or move all business to another supplier are clearly defecting, those whose purchases represent a smaller share of their total expenditures are also "defectors" (Reichheld 1996). For example, Coyles and Gokey (2002) find that 5% of customers at a bank close their checking accounts annually, taking with them 3% of the bank's total balances. However, every year, the 35% of customers who reduced their shares with the bank significantly cost the bank 24% of its total balances. This effect was present in all 16 industries they studied (including airlines, banking, and consumer products) and dominant in two-thirds of them. This suggests that partial defection or silent attrition (Malthouse and Wang 1998) caused by decreasing share of wallet can be more serious than attrition, which is detected only when a customer has decided to no longer use the firm's product or service. Accordingly, marketers need to monitor share of wallet on an ongoing basis, and decreasing share of wallet should be viewed as an early warning signal that a relationship is gradually decaying. Compared with marketing interventions aimed at preventing attrition, marketing efforts that attempt to prevent share-of-wallet losses could be more proactive and, therefore, more effective. Unfortunately, most firms' databases do not contain up-to-date estimates of share of wallet for individual customers.

Share of Category Requirements and Cross-Selling

Since the early 1990s (Kamakura, Ramaswami, and Srivastava 1991), a growing literature has evolved on the topic of cross-selling (Jarrar and Neely 2002; Lau, Chow, and Liu 2004; Lau et al. 2003). This literature is focused on identifying the next product to offer a customer on the basis of the products previously purchased and the patterns of purchase incidence across all customers. More recently, researchers (Kamakura et al. 2003; Li, Sun, and Wilcox 2005) have recognized that customers have multiple relationships and have proposed list augmentation approaches to make cross-selling recommendations that consider the possibility that the customer has already purchased the product elsewhere. To our knowledge, most (if not all) cross-selling models in the marketing literature focus only on the purchase incidence decision. Although cross-selling is an important tool for developing customers, the identification of cross-selling prospects covers only one aspect (purchase incidence) of customer development, overlooking other avenues to enhance the value of a customer. This is particularly true for industries such as banking and retailing, in which customers maintain concurrent relationships with multiple vendors. In these industries, customer relationships can be developed not only by having the customer make purchases in categories in which he or she has not bought before but also by increasing the firm's share of the customer's requirements in categories in which he or she has already made purchases. The list augmentation models we propose and test consider the customer's decision to adopt a product category similar to these cross-selling models, but our models also impute the total volume consumed in the product category and the share of that volume the customer devotes to a particular firm. In other words, we extend the cross-selling models from predicting only the purchase incidence decision to predicting the quantity and incidence decision, thus providing a more informative estimate of a customer's growth potential.

Summary

In light of the foregoing discussion about the advantages and challenges of using share of wallet in CRM, the goal of this article is to develop a predictive model through which a firm can use its internal records, supplemented with a small sample of external records to estimate total and share of requirements in all categories (and, thus, total and share of wallet) for all customers. This enables firms to extend existing customer development initiatives, such as cross-selling, and to benefit from the segmentation, targeting, and attrition detection strategies we discussed previously. Next, we present three models to achieve this aim.

Models for Estimating Total and Share of Category Requirements

The Modeling Task

Consider a firm that offers products in J categories, with transaction records for N customers. The firm knows (1) $Y^1_{nj} \in Y^1$, how much requirements it serves customer n in category j (superscript 1 denotes the focal firm), and (2) $X_n \in X$, a vector of other customer characteristics (e.g., in our empirical illustration, X consists of customer income and length of relationship with the focal firm). The firm does not have information on $Y^0_{nj} \in Y^0$, the size of customer n's requirements in category j served by the firm's competitors (superscript 0 denotes outside the focal firm). To learn about customers' outside requirements Y^0, the firm conducts a survey among a random sample, I, of its N customers. The goal of such a survey is to collect two pieces of information in each product category for each customer i in sample I: the self-reported inside requirements Y^1_{ij} and the self-reported outside requirements Y^0_{ij}. By obtaining self-reported inside requirements, the firm can ensure that they are consistent with their internally recorded counterparts. After data are cleaned to ensure accuracy, the self-reported outside requirements can be linked to records in the firm's customer database. In summary, the firm has complete information (Y^1, Y^0, and X) for only a sample (I) of customers. For the other N – I customers, information on outside requirements, Y^0, is missing. The objective is to develop a model that uses inside requirements, Y^1, and customer characteristics, X, to estimate share of category requirements (S) and total category requirements (T) for these N – I customers, thus augmenting the firm's database with estimates of the customers' relationships with competing firms and, consequently, their potential for growth.

We develop three models to achieve this objective. Model A predicts whether a customer will transact in a category with the focal firm's competitors (i.e., the outside incidence decision) and, if so, the transaction volume (i.e., the outside quantity decision). Model B extends Model A by simultaneously modeling the customers' incidence and quantity decisions both inside and outside the focal firm across multiple product categories, thus explicitly allowing for the possibility that these decisions are correlated. Models A and B can be used to infer the focal firm's share of a customer's category requirements by dividing the customer's inside purchases over the sum of his or her inside and (predicted) outside purchases. In contrast, Model C predicts the share allocation decision directly. It makes three simultaneous predictions: (1) whether a customer will buy in a category, regardless of the vendor (i.e., the category ownership decision), and, if so, (2) the amount to buy in the category (i.e., the total decision) and (3) how large a portion from the focal firm (i.e., the share decision), which can be 0%, 100%, or anything in between.[1] In the empirical section of this study, we calibrate all three models with the same data and compare them on the basis of their predictive performances and managerial interpretability.

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[1] Our approach differs from cross-selling or churn analyses insofar as we jointly forecast category ownership, total, and share of requirements in the context of missing data, whereas the churn models that Neslin and colleagues (2006) report, for example, forecast ownership only in the context of complete data.

Model A: Modeling Incidence and Quantity Outside the Focal Firm

In Model A, we use purchases within the focal firm, along with other customer data available internally, to predict the volume transacted outside the firm. Because the decisions about whether to buy and how much to buy from competitors may be driven by different underlying processes, we propose the following Type II Tobit regression model of incidence and quantity conditional on incidence (Amemiya 1985):

$$(1)\quad \text{if } \eta^*_{ij1} > 0, \text{ then } Y^0_{ij} = \exp(\eta^*_{ij2}); \text{ else } Y^0_{ij} = 0$$

$$\eta^*_{ij1} = \alpha_{j1} + x_i{}'\beta_{j1} + \text{Ind}(Y^1_i)'\gamma_{j01} + \ln(Y^1_i)'\gamma_{j11} + \varepsilon_{ij1}$$

$$\eta^*_{ij2} = \alpha_{j2} + x_i{}'\beta_{j2} + \text{Ind}(Y^1_i)'\gamma_{j02} + \ln(Y^1_i)'\gamma_{j12} + \varepsilon_{ij2},$$

where

- η^*_{ij1} is a latent variable that captures the likelihood of customer i buying in category j from a competing firm. In other words, this latent variable determines the incidence whether customer i has a relationship outside the focal firm in category j;
- Conditional on the customer having a relationship with a competitor, η^*_{ij2} is another latent variable that determines the quantity the customer purchases from the competitor. Because the empirical distributions of conditional quantities are often skewed, they are assumed to be an exponential function of the latent variable and thus enter the likelihood function on a log-transformed scale;
- x_i is a K-element vector of observed characteristics of customer i; $Y^1_i = (Y^1_{i1}, \ldots, Y^1_{iJ})'$; and Ind(·) is an incidence indicator function, such that $\text{Ind}(Y^1_{ij}) = 1$ if $Y^1_{ij} > 0$, else $\text{Ind}(Y^1_{ij}) = 0$;
- ε_{ij1} and ε_{ij2} are normally distributed with the covariance

  $$\begin{pmatrix} \sigma^2_{j1} & r_j\sigma_{j1}\sigma_{j2} \\ r_j\sigma_{j1}\sigma_{j2} & \sigma^2_{j2} \end{pmatrix},$$

  and for identification purposes, we assume that $\sigma_{j1} = 1$ (this covariance structure implies that the incidence and quantity decisions might be correlated, which can occur if there are unobserved factors that affect both decisions); and
- α, β, γ, r, and σ are the model parameters, and there are (2 + 2K + 4J + 2)J of them to be estimated.

Model A is relatively simpler than the subsequent ones in that it models the customer's purchase decision in each category independently. Notably, there are likely to be unobserved factors (which therefore cannot be included in Model A as predictors) that affect customers' purchases from both inside (Y^1_{ij}) and outside (Y^0_{ij}) the focal firm. If the impact of these unobserved factors is substantial, it can lead to biased parameter estimates and, thus, to poor predictions of total and share of category requirements. Nonetheless, we still view Model A as a highly practical solution and a strong benchmark for the other two models we propose because it can be easily estimated as a Type II Tobit regression, and it leads to straightforward data imputations.[2]

Model B: Modeling Incidence and Quantity Inside and Outside the Focal Firm

Model B generalizes Model A by jointly modeling incidence and quantity both inside and outside the focal firm. Modeling decisions inside and outside the firm jointly enable potential correlations between these decisions to be considered. Such correlations might arise from omitted factors that influence inside and outside purchases (e.g., changes in personal status). To the extent that these correlations manifest, inside purchases become informative of outside purchases and therefore can abet the imputation of external demand and customer share. Model B proceeds by assuming that customers make four decisions in each product category: (1) whether to buy from the focal firm; (2) if so, how much; (3) whether to buy from competitors; and (4) if so, how much. Model B allows these decisions to be driven by four different underlying processes that might be correlated not only with one another but also across categories because of the impact of a common set of unobserved customer-specific factors. For example, a recent divorce (for which we do not have data) might lead to reduced purchases from all firms in all categories, suggesting that these decisions could be positively correlated. Formally, we model the incidence and quantity decisions in each category, both inside and outside the focal firm, as follows:

$$(2)\quad \text{if } \eta^*_{ij1} > 0, \text{ then } Y^1_{ij} = \exp(\eta^*_{ij2}); \text{ else } Y^1_{ij} = 0$$

$$\text{if } \eta^*_{ij3} > 0, \text{ then } Y^0_{ij} = \exp(\eta^*_{ij4}); \text{ else } Y^0_{ij} = 0.$$

Equation 2 indicates that customer i's incidence and quantity decisions in category j are determined by four latent variables, η^*_{ij}. The top half of Equation 2 implies that customer i will buy a product in category j from the focal firm if η^*_{ij1} is greater than zero. When this happens, the customer's requirements for the focal firm's product are an exponential function of η^*_{ij2}, which implies that the conditional quantities of inside requirements Y^1_{ij} enter the likelihood function log-transformed. Similarly, the bottom half of Equation 2 states that customer i will buy a product in category j from other firms if η^*_{ij3} is greater than zero, and if so, the customer's requirements served outside the focal firm are an exponential function of η^*_{ij4}.

As indicated previously, we attempt to capture the impact of unobserved customer-specific factors that simultaneously affect customers' incidence and quantity decisions made across product categories and inside and outside the focal firm. Formally, we adopt the following structure on the four latent variables η^*_{ij1}, η^*_{ij2}, η^*_{ij3}, and η^*_{ij4}:

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[2] With the correlation coefficients (r_j) constrained to zero and a logit link function for incidence, Model A is equivalent to a logistic model for the "whether-to-buy" decision coupled with a log-linear regression model for the "how-much-to-buy" decision conditioned on incidence. The results show that Model A and the logistic/log-linear model with no correlations yield largely identical predictions; thus, we do not discuss this null model further.

$$
\begin{aligned}
(3)\qquad \eta^*_{ij1} &= \alpha_{j1} + x_i'\beta_{j1} + z_i'\gamma_{j1} + \varepsilon_{ij1} \\
\eta^*_{ij2} &= \alpha_{j2} + x_i'\beta_{j2} + z_i'\gamma_{j2} + \varepsilon_{ij2} \\
\eta^*_{ij3} &= \alpha_{j3} + x_i'\beta_{j3} + z_i'\gamma_{j3} + \varepsilon_{ij3} \\
\eta^*_{ij4} &= \alpha_{j4} + x_i'\beta_{j4} + z_i'\gamma_{j4} + \varepsilon_{ij4},
\end{aligned}
$$

where

- x_i is defined as previously, a K-element vector of observed characteristics of customer i;
- z_i is a P-element vector that captures unobserved, individual-specific factors that affect the incidence and quantity decisions of customer i; each element of z_i is assumed to be i.i.d. standard normal; ε_{ij1}, ε_{ij2}, ε_{ij3}, and ε_{ij4} are the stochastic components in each decision that are normally distributed with variances σ^2_{j1}, σ^2_{j2}, σ^2_{j3}, and σ^2_{j4}, respectively; for identification purposes, it is assumed that $\sigma_{j1} = \sigma_{j3} = 1$; and
- α, β, γ, and σ are the model parameters; P, the dimensionality of unobserved customer factors, is to be determined empirically; given K, P, and J, ([1 + K + P] × 4 + 2)J parameters need to be estimated.

The foregoing structure provides a parsimonious representation of the correlation pattern between the 4 × J (i.e., the number of decisions in each category times the number of categories) latent variables, η^*_i. Substantial parsimony will be gained when J is large and decisions across these categories are interrelated. As with Model A, a caveat of Model B is that its parameter estimates cannot be directly interpreted to learn about how customers decide share allocations across vendors. Accordingly, in Model C, we model customers' share decisions explicitly.

Model C: Modeling Category Ownership, Total, and the Focal Firm's Share

In Model C, we develop an approach that can be used to predict a customer's category demand and the focal firm's share directly when only inside purchases are recorded. Our motivation for developing such a model is twofold. First, we want to understand how observed customer characteristics affect the total and share-of-category-requirements decisions. This is important because different customer characteristics may be related to a customer's category demand and share allocation in different ways, and marketers who are interested in understanding these relationships can use such insights to devise customer development strategies accordingly. The second reason for modeling total and share of category requirements explicitly is that such a specification aligns itself well with the choice-modeling literature that decomposes consumer purchase decisions into "incidence, quantity, and choice" (Gupta 1988), in which consumers decide whether to buy in a category and, if so, how much and, finally, which brands to choose. In Model C, we attempt to decompose customers' category requirement decisions in a similar way—namely, "ownership, total, and share." Of note, our approach and context is different from that of Gupta (1988) and others insofar as (1) the goal is to impute these decisions with incomplete information, (2) we consider these decisions made across multiple categories, and (3) the choice and share decisions require different treatments.

Consequently, Model C assumes that a customer faces decisions of ownership (whether to own a product category), total (the total category requirements if he or she decides to own), and share (the share of the total requirements, if any, to be served by the focal firm). Formally,

$$
\begin{aligned}
(4)\qquad & \text{if } \eta^*_{ij1} > 0, \text{ then } T_{ij} = \exp(\eta^*_{ij2}); \text{ else } T_{ij} = 0 \\
& \text{if } \eta^*_{ij3} \le 0, \text{ then } S_{ij} = 0; \text{ else if } \eta^*_{ij3} \ge 1, \text{ then } S_{ij} = 1; \\
& \qquad \text{else } S_{ij} = \eta^*_{ij3}.
\end{aligned}
$$

Equation 4 posits that customer i's purchase decisions in category j are governed by three latent variables, η^*_{ij}. The top portion of Equation 4 states that the customer will buy a product in the category only if η^*_{ij1} is greater than zero (i.e., category ownership), and when this happens, the customer's total requirements T_{ij} are an exponential function of η^*_{ij2}, which implies that the conditional quantities of total requirements T_{ij} enter the likelihood function log-transformed. The bottom portion of Equation 4 implies that the customer will allocate some of his or her purchases to the focal firm if η^*_{ij3} is greater than zero. When this happens, the customer might have all his or her requirements served by the focal firm (if η^*_{ij3} is greater than or equal to one) or a share of them that is equal to η^*_{ij3}. Thus, we model share of category requirements as a distribution truncated at 0 and 1. Furthermore, we assume that the three latent variables η^*_{ij1}, η^*_{ij2}, and η^*_{ij3} are functions of a common set of factors, observed and unobserved, with a structure as follows:

$$
\begin{aligned}
(5)\qquad \eta^*_{ij1} &= \alpha_{j1} + x_i'\beta_{j1} + z_i'\gamma_{j1} + \varepsilon_{ij1} \\
\eta^*_{ij2} &= \alpha_{j2} + x_i'\beta_{j2} + z_i'\gamma_{j2} + \varepsilon_{ij2} \\
\eta^*_{ij3} &= \alpha_{j3} + x_i'\beta_{j3} + z_i'\gamma_{j3} + \varepsilon_{ij3},
\end{aligned}
$$

where

- x_i and z_i are defined as previously, denoting K observed characteristics and P unobserved factors, respectively, associated with customer i, with each element of z_i assumed to be i.i.d. standard normal; z_i can also be interpreted in the terminology of factor analysis as customer i's scores on P latent factors, in which γ_j are the factor loadings (which we demonstrate how to interpret in the "Results" section); ε_{ij1}, ε_{ij2}, and ε_{ij3} are the stochastic components in each decision, normally distributed with variances σ^2_{j1}, σ^2_{j2}, and σ^2_{j3}, respectively;[3] for identification purposes, we assumed that $\sigma_{j1} = 1$; and
- α, β, γ, and σ are the model parameters; P, the dimensionality of unobserved customer factors, is to be determined empirically; given K, P, and J, ([1 + K + P] × 3 + 2)J parameters need to be estimated.

We denote the variance–covariance matrix of the latent vector η^*_i as $\Lambda(3J \times 3J)$, arising from 3 decisions by J categories. Thus, for the jth and gth categories (j and g in J) and the hth and lth decisions (ownership, total, or share), the foregoing structure implies that the variance and covariance between η^*_{ijh} and η^*_{igl} can be expressed as follows:

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[3] White tests for heteroskedasticity on the log-transformed nonzero balances show that the residuals of the model are not a function of the predicted log total balances, which indicates that the homoskedasticity assumption with regard to the stochastic components conforms to the data.

$$(6)\ \text{var}(\eta^*_{ijh}) = \gamma'_{jh}\gamma_{jh} + \sigma^2_{jh} \text{ or } \text{cov}(\eta^*_{ijh}, \eta^*_{igl}) = \gamma'_{jh}\gamma_{gl}.$$

Equation 6 depicts the role of γ, the $3J \times P$ factor loadings, in reducing a large $3J \times 3J$ variance–covariance matrix into a smaller $3J \times P$ factor space as $\Lambda = \gamma \times \gamma' + \Sigma$, where Σ is a diagonal matrix with σ^2_{jh} as entries. As such, the structure depicted in Equation 5 provides a parsimonious representation of the nature and strength of the correlations between $3 \times J$ decisions, namely, ownership, total, and share decisions made by each customer in J product categories. Moreover, the estimates of factor loadings lend themselves to substantive interpretation and graphical display, which we illustrate subsequently in our application. Detailed procedures for estimating this model and for imputation appear in Appendixes A and B, respectively.

Data for Empirical Illustration

Data Collection

A major U.S. bank provided the data we used for our empirical illustration. This bank provided us with information for 34,142 of their customers regarding their balances outside the bank in ten categories (Y^0_1, ..., Y^0_{10}), including noninterest checking, interest checking, savings, certificates of deposit (CDs), personal managed investments, car loan, personal loan, line of credit, credit card loan, and mortgage. A third-party research firm compiled these data in an ongoing market audit study. Each observation from this audit details when the information was collected, and only households that had at least one account with positive balance with the bank were included to ensure that these customers were active. For the periods during which the market audits were conducted (i.e., from 1999 Q3 to 2002 Q2, with approximately 4500 households each quarter), this information on customer external relationship was aligned with records on the balances these households had inside the bank in the ten categories (Y^1_1, ..., Y^1_{10}), thus providing a unique data set that includes both total (T_1, ..., T_{10}) and share of (S_1, ..., S_{10}) category requirements.

The data set provided by the bank also contains two observed customer characteristics—annual household income and customer tenure—that we use as predictor variables (x_1 and x_2, respectively) in the empirical illustration of our proposed models.[4] Household income is pretax and includes income from both salaries and interest and investment returns. Income-related information is garnered from multiple sources, including Acxiom and customer self-reports (e.g., loan applications), and it is updated periodically through a proprietary "householding" process. Given its skewed nature, household income is log-transformed. Customer tenure is measured in the number of years since the first account was opened at the focal bank.

Because most firms in other industries would not have the benefit of market audit studies conducted by a third-party research supplier, they would need to conduct a survey (often anonymously) on their own with a sample of their customers to obtain data on the volume of business these customers do with competitors. For this sample of customers, with complete information on their relationships with the firm and its competitors, our proposed models can be calibrated and then used to impute total and share of category requirements for all customers. To improve the accuracy of the imputation results, it is desirable to check for self-reporting errors in the survey data. Because firms cannot obtain transactional data from their competitors, it is difficult to check directly the error rates in the sample customers' self-reported data on the business they transact outside the focal firm. An indirect approach is to collect self-reported data on the business the sample customers transact inside the focal firm and to ensure that these data align with internal records. Accordingly, we compared the account balances inside the bank, which we obtained from internal records, with the customers' self-reports, which we obtained through the market audit study. We found little systematic discrepancies; the mean reporting error (market audit reports – internal records) is not significantly different from zero in nine of the ten categories, except for that of savings. Therefore, we presume that the balances outside the bank from the market audit study also exhibit little systematic error.

Study Design

We apportion our data randomly into a calibration sample composed of 23,957 customers and a validation sample of 10,185 customers. This apportionment is intended to reflect the data available to firms in practice, in which they have complete data for only a subset of their customers (analogous to the calibration sample) and incomplete data for the rest of their customer base (analogous to the validation sample).[5] Accordingly, for the calibration sample, we use all the information available, including account balances inside the focal bank (Y^1), household income (x_1), and customer tenure (x_2), as well as account balances outside the focal bank (Y^0). The validation sample mimics the remainder of the customer base for whom the focal bank does not know balances the customers might keep with competitors. We first use the calibration sample to fit the proposed models. Then, in the validation sample, we apply the calibrated models to the internal data (i.e., inside balances, household income, and customer tenure) to impute the outside balances and therefore predict total (T) and share of (S) category requirements. Finally, we evaluate the models' predictive performances in the validation sample by comparing

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[4] We do not have data for additional behavioral variables, such as the number of branch visits and checks withdrawn. However, the variables we do employ (income and tenure) generalize beyond the banking industry. Adding industry-specific variables as predictors would serve to increase the effectiveness of our approach.

[5] Many firms may not be able to afford a large-scale survey on customers' external transactions. In such cases, because of its efficiency, K-fold cross-validation could be more preferable than the holdout sample cross-validation.

TABLE 1
Structure of the Data Set Used in Empirical Illustration

	Inside the Bank	Outside the Bank
Calibration Sample with 23,957 Customers		
Total and share of category requirements available by combining internal balances with external balances from a market audit study conducted by a third-party research firm	Internal balances in ten accounts Household income Length of relationship with the bank	External balances in ten accounts from the market audit study (Thus, total and share of category requirements observed)
Validation Sample with 10,185 Customers		
Mimicking the remainder of the customer base in which information on total and share of category requirements is unavailable	Internal balances in ten accounts Household income Length of relationship with the bank	Total and share of category requirements to be imputed (Performance evaluated in relation to available data from the market audit study)

the imputed T and S against their observed counterparts. Table 1 summarizes this design.

Summary Statistics

Table 2 reports several summary statistics of the data for both the calibration and the validation samples. Not surprisingly, the two subsamples are similar. Column 2 shows the average category ownership of each type of product. Column 3 shows the average total balances conditional on ownership. Among customers who have positive total balances, Column 4 shows the percentage of customers who have zero balance with the focal bank (thus, share = 0). Column 5 reports the percentage of customers who have positive balances both inside and outside the bank (thus, 0 < share < 1). Approximately 60% of the bank's customers have financial assets inside and outside the bank. Similarly, approximately 50% of the bank's customers have financial debts both inside and outside the bank. Column 6 shows the percentage of customers who are exclusive customers of the focal bank (thus, share = 1). Approximately one in five of the bank's customers have 100% of their requirements for financial assets served by the bank. Fewer than one in ten do so when it comes to fulfilling requirements for financial debts. Together, Columns 4–6 suggest the importance of treating the distribution of share decisions as truncated at both 0 and 1.

Finally, Column 7 shows the bank's average share of requirements in each category. The bank's deposit products (interest and noninterest checking, savings, and CDs) perform best in terms of obtaining a large share of customers' business. Loan products, except for line of credit, have much smaller shares than deposit products. The bank performs most poorly with respect to attracting customers' investment dollars. Taking this information as a whole, the bank has only approximately 20% of its existing customers' total wallet, reflecting high competitive intensity in many of the bank's categories. This competition amplifies the need to use accurate estimates of share of category requirements to ascertain potential targets across the bank's spectrum of product categories.

The other two variables included in our empirical illustration are the customers' household income and tenure with the focal bank. The mean, median, and standard deviation of income are $54,566, $48,086, and $36,198, respectively, for the calibration sample and $54,859, $48,776, and $35,684, respectively, for the validation sample. The mean, median, and standard deviation of customer tenure (in years) are 9.4, 10, and 3.8, respectively, for the calibration sample and 9.2, 10, and 3.9, respectively, for the validation sample.

Results

Model Comparison

We begin our analysis by comparing the predictive performances of Models A, B, and C in the validation sample. As a basis for comparison, we also consider a log-linear regression of the form $\ln(Y^0_{ij} + 1) = \alpha_j + x_i'\beta_j + \text{Ind}(Y^1_i)'\gamma_{j0} + \ln(Y^1_i)'\gamma_{j1} + \varepsilon_{ij}$, $\varepsilon_{ij} \sim N(0, \sigma^2_j)$, because this model can be readily estimated with ordinary least squares.

We consider the ability of each model to predict total and share of category requirements for each separate category, as well as for all assets together, all debts together, and all categories as a whole (i.e., share of wallet and total wallet). We consider three dimensions: outside product ownership, total category requirements (wallet size), and share of category requirements (share of wallet). As Table 3, Panels A and B, indicate, the log-linear model's performance on these dimensions is dominated by the other models. Given that Model A, similar to the log-linear model, can be estimated using off-the-shelf software and dominates the latter, we refrain from further discussion of the log-linear model. We organize our discussion by each dimension.

Predicting outside product ownership. Table 3, Panel A, compares the models' abilities to predict outside product

TABLE 2
Sample Summary Statistics

Product Category	Percentage of Customers with Positive Total Category Requirements		Average Total Category Requirements ($)[a]		Percentage of Customers with Share of Category Requirements = 0[a]		Percentage of Customers with 0 < Share of Category Requirements < 1[a]		Percentage of Customers with Share of Category Requirements = 1[a]		Average Share of Category Requirements[a]	
Subsample[c]	**Calibration**	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**
Total assets	99.8	99.7	95,191 (226,315)[b]	91,936 (212,861)[d]	20.3	20.1	60.0	59.4	19.7	20.5	17.3	17.3
Noninterest checking	60.4	60.4	5,697 (9,264)	5,810 (10,694)	29.6	29.2	18.8	18.8	51.5	52.0	54.6	55.4
Interest checking	52.0	51.7	10,315 (20,862)	9,420 (17,317)	38.9	38.4	17.3	16.9	43.8	44.6	48.4	49.9
Savings	79.5	79.4	19,912 (56,922)	18,800 (44,414)	43.2	42.8	23.6	24.6	33.2	32.6	36.0	36.2
CDs	19.4	20.2	49,126 (94,765)	48,396 (99,631)	52.7	54.6	13.2	11.4	34.1	34.0	35.1	32.4
Investments	55.8	55.3	108,940 (242,226)	105,996 (231,246)	89.0	89.0	6.5	6.2	4.5	4.9	4.8	4.9
Total debts	87.3	87.2	79,857 (112,534)	78,931 (108,140)	43.4	43.7	48.4	48.3	8.2	8.0	22.4	22.5
Car loan	46.3	46.7	14,106 (12,095)	14,065 (11,986)	80.9	81.6	5.9	5.6	13.3	12.8	14.6	14.2
Personal loan	24.8	24.7	18,746 (29,687)	18,637 (26,938)	81.3	80.5	4.2	4.5	14.5	15.0	16.7	17.2
Line of credit	18.7	18.1	10,521 (24,737)	10,578 (32,399)	50.0	50.7	7.2	7.5	42.8	41.8	39.9	43.3
Credit card	66.3	65.7	4,713 (7,621)	4,682 (6,901)	60.8	60.5	26.0	26.2	13.1	13.3	18.1	17.9
Mortgage	52.1	52.3	102,546 (117,592)	100,760 (111,205)	74.0	73.5	2.0	2.0	24.0	24.5	23.5	23.5

[a] For customers whose total account balances are greater than zero.

[b] Standard deviation is in parentheses.

[c] Number of customers in the calibration sample = 23,957; number of customers in the validation sample = 10,185.

[d] The balances used in estimation are log-transformed to mitigate considerations pertaining to extreme values, and as a result, the standard deviations of the log-transformed balances are smaller than the means, and the means and standard deviations are relatively equal across all product categories.

ownership in terms of the hit rate (i.e., the percentage of true positives and negatives), the percentage of false positives, and the percentage of false negatives.[6] The results show that all three models perform equally well in terms of predicting whether a customer has positive balances outside the bank in a particular category; hit rates, false-positive rates, and false-negative rates average approximately 72~73%, 11~12%, and 16~17%, respectively.

Predicting total category requirements. To compare the models' performance in predicting total category requirements, we calculate the mean absolute deviation (MAD) of the predicted total category requirements.[7] To reflect the variability inherent in our data, we also calculate the MAD for a naive model, in which the predicted total category requirements are simply the account balances inside the bank plus the average account balances outside the bank. Table 3, Panel B (Columns 2–6), reports the naive model's MAD and the percentage improvement (reduction) in MAD relative to the naive model for the various predictive models (which is equal to 1 – MAD_Model/MAD_Naive). The results show that Model C performs much better than Models A and B in predicting the exact sizes of total category requirements (or, equivalently, requirements served outside the focal bank). This is the case for total wallet, total assets, and total debts, as well as for all ten individual product categories.

Predicting share of category requirements. For this comparison, we calculate the MAD of the predicted share of category requirements. By definition, for a category with a zero account balance in the focal bank, share of requirements for that category is either zero (when balance outside the bank in the category is greater than zero) or not defined (when balance outside the bank in the category is also zero); consequently, accuracy in predicting share of requirements for a particular category is relevant only with respect to observations for which there is a positive account balance in that category in the focal bank. Again, as a reference, we use a naive model in which predicted share of category requirements is equal to account balances inside the bank divided by the sum of account balances inside the bank and the average account balances outside the bank. Table 3, Panel B (Columns 7–11), reports the MAD of the naive model, along with the percentage improvement (reduction) in MAD relative to the naive model for the various predictive models. Again, Model C outperforms Models A and B in predicting share of category requirements, which is the case for total wallet, total assets, and total debts, as well as for nine of the ten individual product categories. To our surprise, in eight of the ten categories, the simpler Model A does better than the more sophisticated Model B.

Taking the model comparison results reported in Table 3, Panels A and B, as a whole, we conclude that if the goal is simply to predict whether a customer uses a product offered by the competition (i.e., the cross-selling prediction that Kamakura et al. [2003] propose), any of the three models would be sufficient. Conversely, if the goal is to predict the sizes of total and share of category requirements, Model C is more accurate than the other models. Given that (1) total and share of category requirements are central to assessing customer potential, (2) Model C's parameter estimates can be readily interpreted to gain insights into customers' total and share decisions, and (3) Model C provides the best prediction overall, we believe that Model C has the greatest utility for imputing total and share of category requirements.[8] As such, to conserve space, we subsequently focus on the estimation results for Model C. (Parameter estimates for Models A and B are available on request.)

Estimation Results for Model C

Estimation of Model C from the calibration sample for $P = 0$–3 latent factors leads us to choose the model with $P = 2$. The Bayesian information criteria (BICs) for Model C with $P = 0, 1, 2$, and 3 and for the other two models appear in Table 4. Parameter estimates of the two-factor ($P = 2$) Model C appear in Table 5, Panel A (which includes the intercepts, α, and the coefficients on customer income and tenure, β) and Panel B (which reports the factor loadings, γ).

Income. Table 5, Panel A, indicates that customer income positively and significantly correlates with both ownership and total decisions across the product categories. Customers with higher incomes are more likely to own assets and debts (e.g., $\beta_{1,\text{income}} = .49$ for savings, $p < .01$) and have higher requirements when they own them (e.g., $\beta_{2,\text{income}} = .86$ for savings, $p < .01$). Customers with higher incomes also have a significantly smaller share of their requirements for financial products with the bank under study (e.g., $\beta_{3,\text{income}} = -.54$ for savings, $p < .01$). We conjecture that there could be many causes for this result. First, with greater requirements for financial products (Asher 2001; Barr 2004) and fewer restrictions (Sharir 1974; Zeithaml 1985), high-income customers stand to gain more by spreading their "nest eggs" across more financial institutions. Second, competition may be more intense for the high-income households' wallets (Bielski 2004), giving them more incentives and opportunities to fulfill their requirements at multiple competing institutions. Third, customer loyalty and satisfaction have been shown to be negatively linked to or moderated by income (Cooil et al. 2007; Homburg and Menon 2003; Korgaonkar, Lund, and Price 1985; Zeithaml 1985). Finally, the bank under study may be comparatively less preferred by its higher-income clientele, for example, because of a weak market position relative to

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[6] A hit occurs either when the customer has positive external balances and the model predicts that the likelihood of this occurrence will exceed 50% or when the customer has zero balances outside the bank and the model predicts that the likelihood of positive external balances will be below 50%. Depending on the relative costs of misclassification (false positive versus false negative), the threshold (50%) can be adjusted upward or downward.

[7] We also calculated the MAD of the log-transformed predicted total category requirements, and the performance of Model C remained much better than the other two models.

[8] We also estimated Model C with customer income and tenure omitted. The results indicate that most of the model's predictive power arises from internal transactions rather than demographic variables, such as income or tenure.

TABLE 3
Performance Comparisons in the Validation Sample

A: Predicting Outside Product Ownership

	Hit Rate				False-Positive Rate				False-Negative Rate			
	Log-Linear	Model A	Model B	Model C	Log-Linear	Model A	Model B	Model C	Log-Linear	Model A	Model B	Model C
Total Wallet	.37	.73	.72	.72	.63	.11	.11	.12	.00	.16	.17	.16
Total Assets	.38	.73	.72	.72	.62	.11	.11	.12	.00	.16	.17	.16
Noninterest checking	.33	.71	.69	.70	.67	.09	.06	.05	.00	.20	.25	.25
Interest checking	.32	.74	.72	.72	.67	.08	.07	.13	.00	.18	.21	.15
Savings	.54	.66	.64	.64	.46	.19	.22	.23	.00	.15	.14	.13
CDs	.16	.87	.87	.86	.84	.01	.01	.01	.00	.12	.12	.13
Investments	.55	.68	.68	.67	.45	.19	.20	.21	.00	.13	.12	.12
Total Debts	.37	.73	.71	.73	.63	.11	.11	.11	.00	.16	.18	.16
Car loan	.42	.63	.62	.63	.57	.13	.13	.12	.00	.24	.25	.25
Personal loan	.23	.79	.79	.79	.77	.01	.01	.01	.00	.20	.20	.20
Line of credit	.18	.89	.89	.89	.82	.01	.01	.02	.00	.10	.10	.09
Credit card	.57	.62	.61	.61	.43	.27	.29	.28	.00	.11	.10	.11
Mortgage	.46	.71	.65	.71	.54	.13	.12	.13	.00	.16	.23	.16

B: Predicting Total and Share of Category Requirements

	Predicting Total Category Requirements					Predicting Share of Category Requirements				
		Percentage Improvement in MAD					Percentage Improvement in MAD			
Measure	Naive MAD	Log-Linear (%)	Model (%)	Model B (%)	Model C (%)	Naive MAD	Log-Linear (%)	Model A (%)	Model B (%)	Model C (%)
Total Wallet	125,020	5	6	10	15	.21	6	7	8	12
Total Assets	93,177	4	5	11	18	.39	9	10	11	15
Noninterest checking	2357	10	10	9	17	.34	22	22	17	31
Interest checking	3698	10	11	13	22	.37	24	26	21	37
Savings	13,426	4	4	15	23	.48	21	21	17	37
CDs	11,609	9	10	18	25	.45	16	17	28	36
Investments	76,158	1	2	7	12	.42	4	6	0	15
Total Debts	60,238	8	9	6	14	.26	16	17	0	18
Car loan	7315	7	8	9	11	.33	10	10	–16	15
Personal loan	6222	3	3	6	8	.32	12	13	7	26
Line of Credit	1972	2	–5	–1	5	.39	20	17	25	47
Credit card	3038	7	8	6	8	.37	7	9	8	15
Mortgage	54,322	6	8	3	13	.22	27	30	–116	28

TABLE 4
Fit Measures for the Predictive Models in the Calibration Sample

Number of Factors	Model A Not Applicable	Model B P = 0	Model B P = 1	Model B P = 2[a]	Model B P = 3	Model C P = 0	Model C P = 1	Model C P = 2[a]	Model C P = 3
Number of parameters	460	140	180	220	260	110	140	170	200
BIC	529,695	895,825	878,446	870,232	870,528	838,238	819,865	811,907	811,961

[a]The smallest BIC and, thus, the number of factors chosen.

TABLE 5
Model C Parameter Estimates

A: Observed Customer Characteristics (Number of Parameters = 90)

Category	Ownership α_1 Intercept	Ownership β_1 Income[a]	Ownership β_1 Tenure	Total (Conditional on Ownership) α_2 Intercept	Total (Conditional on Ownership) β_2 Income	Total (Conditional on Ownership) β_2 Tenure	Share (Conditional on Ownership) α_3 Intercept	Share (Conditional on Ownership) β_3 Income	Share (Conditional on Ownership) β_3 Tenure
Noninterest checking	**.78**	**.07**	–.09	**8.01**	**.63**	**.05**	**1.04**	**–.61**	**.56**
Interest checking	**.16**	**1.12**	**.37**	**7.88**	**.76**	**.22**	**.46**	**–.65**	**.75**
Savings	**.91**	**.49**	**.06**	**8.39**	**.86**	**.38**	**.42**	**–.54**	.27
CDs	**–.96**	**.20**	**.24**	**9.59**	**.24**	**.29**	–.03	**–.76**	**.43**
Investments	**.14**	**.79**	**.09**	**9.99**	**1.06**	**.49**	**–2.51**	**–.26**	**.41**
Car loan	**–.09**	**.51**	**–.20**	**9.07**	**.33**	–.02	**–3.64**	**–.39**	–.07
Personal loan	**–.70**	**.28**	**–.20**	**9.09**	**.29**	.02	**–4.75**	**–1.00**	**1.68**
Line of credit	**–.96**	**.41**	**.11**	**7.88**	**.57**	**.25**	**1.18**	**–1.99**	**2.01**
Credit card	**.45**	**.24**	**–.08**	**7.71**	**.41**	.00	**–.31**	**–.14**	.19
Mortgage	**.03**	**.78**	**.11**	**10.79**	**.51**	**–.15**	**–10.53**	–.40	**–.61**

B: Factor Loadings and Variances (Number of Parameters = 80)

Category	Ownership Decision $\gamma_{1,1}$ Factor 1 Loading	Ownership Decision $\gamma_{2,1}$ Factor 2 Loading	Total (Conditional on Ownership) $\gamma_{1,2}$ Factor 1 Loading	Total (Conditional on Ownership) $\gamma_{2,2}$ Factor 2 Loading	Total (Conditional on Ownership) σ_2 SD	Share (Conditional on Ownership) $\gamma_{1,3}$ Factor 1 Loading	Share (Conditional on Ownership) $\gamma_{2,3}$ Factor 2 Loading	Share (Conditional on Ownership) σ_3 SD
Noninterest checking	**–2.76**	**–.30**	–.01	.00	**1.05**	**.16**	**–1.20**	**1.52**
Interest checking	**4.01**	**1.15**	**.67**	**.14**	**1.04**	**.75**	**–1.75**	**1.23**
Savings	**.16**	**.27**	**.50**	**.12**	**1.48**	**.31**	**–1.45**	**.70**
CDs	**.34**	**.15**	**.40**	**.09**	**1.28**	**.49**	**–2.01**	**2.09**
Investments	**.10**	**.16**	**.42**	**.13**	**1.53**	**.49**	**–.50**	**1.94**
Car loan	**–.25**	**–.17**	**–.03**	.00	**.97**	–.11	**.81**	**4.03**
Personal loan	**–.21**	**–.17**	–.02	**–.04**	**1.19**	**1.36**	**–.49**	**5.68**
Line of credit	–.03	**–.18**	**.09**	**.07**	**1.51**	**.95**	**–4.12**	**3.43**
Credit card	**–.21**	**–.22**	**–.12**	–.15	**1.12**	**.09**	–.02	**1.11**
Mortgage	**–.14**	**–.23**	–.02	**–.09**	**1.36**	**1.97**	**3.43**	**15.66**

[a]Income was log-transformed.

Notes: Parameter estimates that are significant at $p < .01$ are in bold.

other nonretail bank providers. In any case, the bank should attend to its lower share of its higher-income customers' wallets and determine whether it should use better-targeted marketing treatments to redress this unfavorable position.

Tenure. The relationship between customer tenure and the customer ownership, total, and share decisions is less clear. Longer tenures are associated with a larger share of customers' checking, CD, investment, personal loan, and line-of-credit balances (as reflected in the positive and significant $\beta_{3,\text{tenure}}$). In contrast, there is no significant correlation between customers' tenure and the bank's share of their savings, car loan, and credit card balances (as reflected in the insignificant $\beta_{3,\text{tenure}}$). For customers with longer tenures, the bank has a smaller share of their mortgages ($\beta_{3,\text{tenure}} = -.61$, $p < .01$). The lack of a positive relationship between customer tenure and customer share in certain categories (Cooil et al. [2007] also find this for another financial institution) may deserve the bank's close attention because it may imply that lengthening the relationship with customers does not necessarily translate into a larger share of the customers' business in these categories. To pinpoint the dynamics between customer tenure and customer share (Keiningham, Vavra, et al. 2005), however, the bank needs to collect longitudinal data on customer share (instead of using only cross-sectional data).

Factor loadings. Of the 60 estimated factor loadings that appear in Table 5, Panel B, 52 are significant at the $p < .01$ level, indicating that the latent factor structure captures unobserved individual-specific factors that have caused the correlations among ownership, total, and share decisions in the various product categories. To visualize these correlations, Figure 2, Panels A and B, plots the factor loadings from Table 5, Panel B. The rendering of correlation patterns yields managerial insights into customers' ownership, total-wallet, and share-of-wallet decisions among the bank's services. For example, a positive correlation between two ownership decisions means that a customer who is more likely to own one service is also more likely to own another. In Figure 2, Panels A and B, any two vectors pointing in the same (or opposite) direction indicate that decisions these vectors represent are positively (or negatively) correlated; two vectors that are orthogonal to each other imply that the corresponding decisions are independent of each other. We standardized all the factor loadings plotted in the figure so that the length of the vectors and the angle between them directly reflect the strength of correlation between the decisions they represent.

Figure 2, Panel A, captures correlations between the ownership and the total-requirements decisions. Several points are noteworthy:

- There is an assets-versus-debts dimension in terms of the total-requirements decisions. Interest checking, savings, CD, and investment decisions point in one direction, and credit card, mortgage, and personal loan decisions point in the other direction. Thus, all else being equal, customers with more financial assets have fewer debts (except for line of credit). This also provides face validity for the correlation results;
- In terms of the ownership decision, customers who own a noninterest checking and/or a debt account are less likely to own an interest checking account. Ownership of interest checking, savings, CD, and investment accounts are positively correlated, thus reflecting some customers' propensities to save. Similarly, customers with one type of debt are more likely to have other types of debt and are less likely to have financial assets (except for noninterest checking); and
- The same factors that induce customers to assume debt lead them to be deeper in debt (vectors representing debt ownership and total debt point in the same direction). A similar relationship exists for assets.

More germane to targeting customers with high growth potential, the factor loadings plotted in Figure 2, Panel B, depict the correlations between total-requirements and share-of-requirements decisions across various product categories, suggesting the following:

- Typically, share decisions are positively correlated across product categories, except for car loans. Thus, customers who do the bulk of transactions with the bank in one category also tend to do so in others, suggesting the potential for positive externalities across categories;
- In five of the ten categories (i.e., interest checking, savings, CDs, investments, and car loans), the bank has been efficient in targeting in the sense that the bank has larger shares of customers with larger requirements;
- However, for line of credit, total and share of requirements are independent. This implies that the bank might not be targeting high-volume customers to promote its line of credit; and
- For personal loans, credit card, and mortgage, share of category requirements and total category requirements are negatively correlated. This suggests that the focal bank has a low share among high-requirement customers in these three categories. Thus, these customers represent potentially attractive targets.

Testing the Targeting Efficiency of Our Recommended Approach

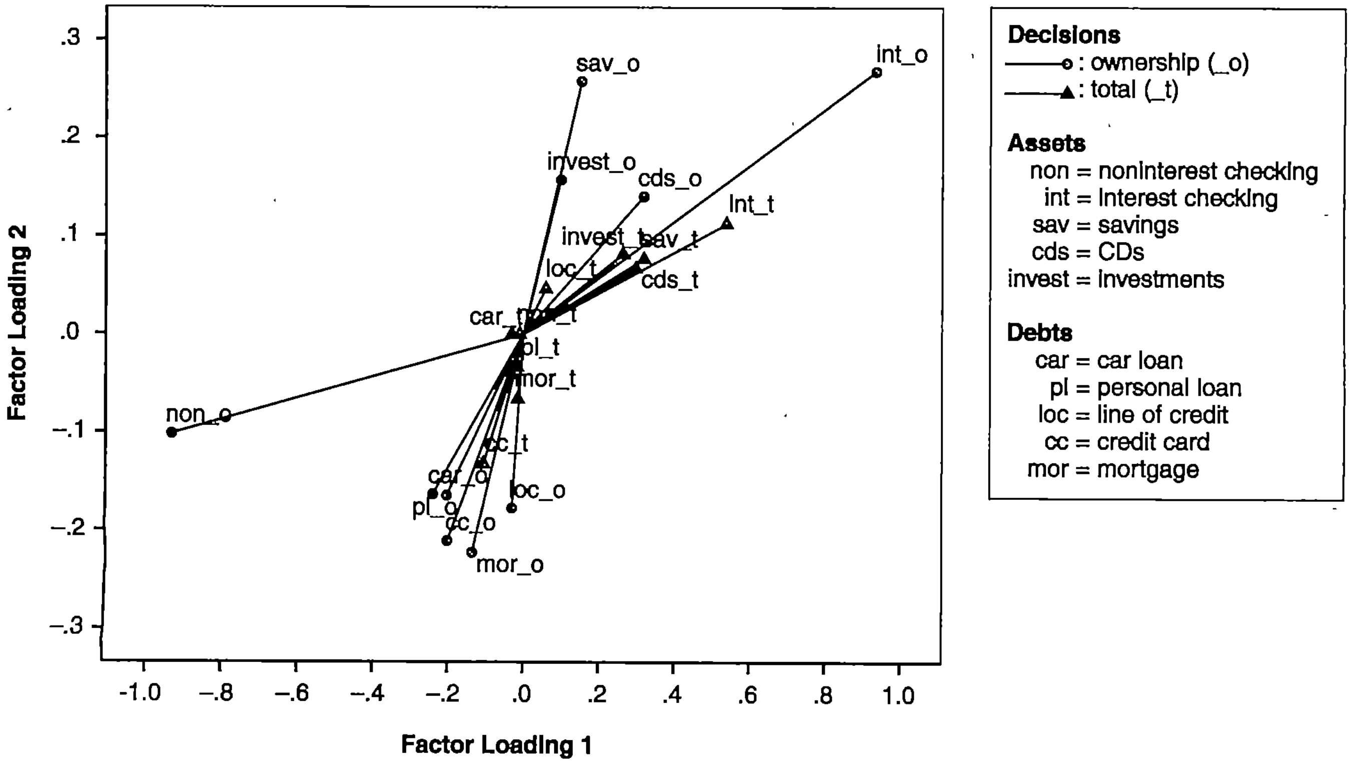
To ascertain the efficacy of Model C for targeting customers with large total requirements but small current shares, we assess Model C's ability to identify customers whose total assets (i.e., sum of checking, savings, CDs, and investments) are in the top quintile but the bank's shares are lower than average. Such customers could be denoted as being "platinum" in growth potential under Rust, Zeithaml, and Lemon's (2000) "customer pyramid" framework. We explore Model C's ability to identify these customers by applying the calibrated model to the validation sample and predicting who is in this platinum-potential segment. We then compare these predictions with the actual data.

Although customers we predicted to have platinum potential (i.e., the top quintile in total assets but lower than average shares with the focal bank) constitute only 12% of the validation sample, they account for 37% of the validation sample's assets outside the bank. This leads to a lift of 37%/12% = 3.1 for Model C. Comparable lifts for Models A and B are 2.6 and 2.5, respectively. Using the observed data to identify the platinum-potential segment (i.e., perfect hindsight and maximum lift achievable) yields a lift of 4.7. Together, these results suggest that our list augmentation approach enables firms to target customers with high potential for short-term growth and that Model C performs better than Models A and B at this task.

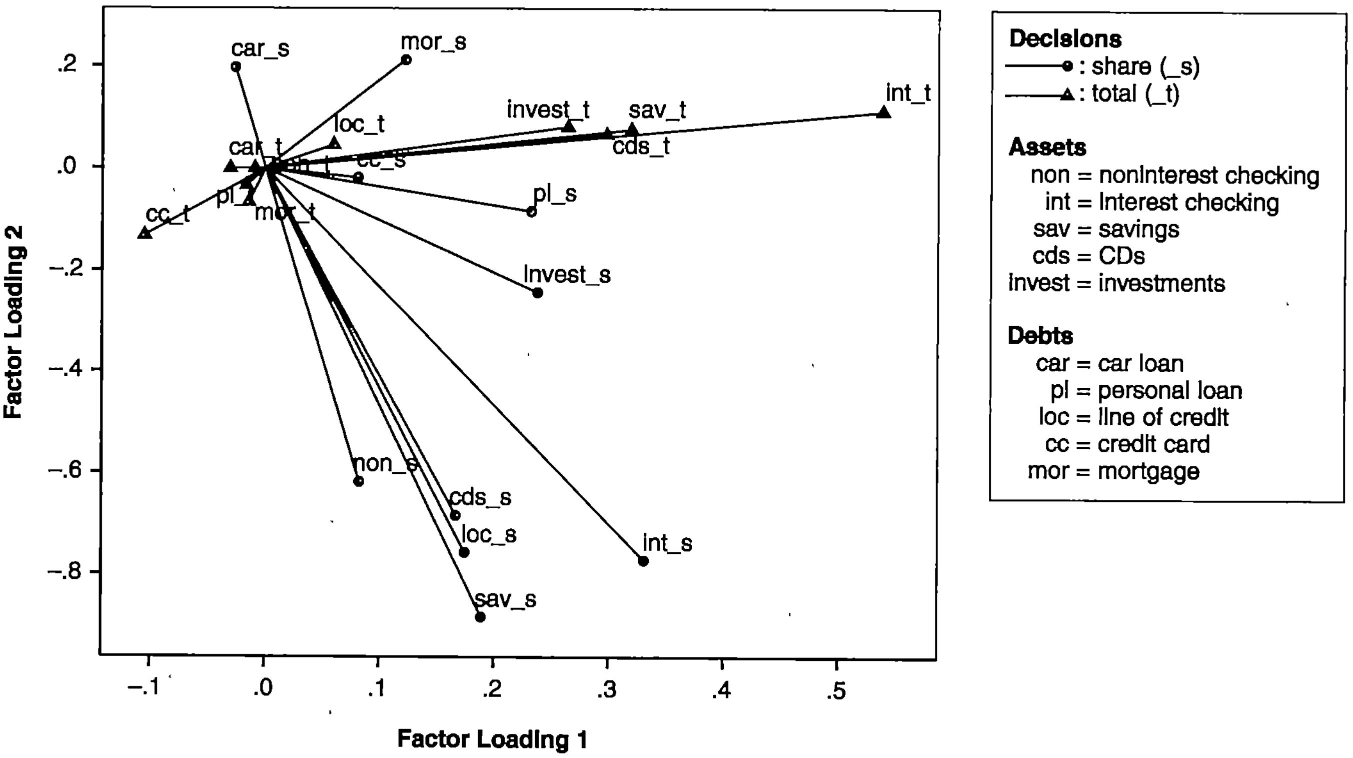
Similar targeting exercises can also be performed for total debts or on a category-by-category basis. For example, compared with other categories, the focal bank has the smallest share of its customers' investment dollars (see Table 2). Model C suggests that if the bank targets customers whose requirements for investment products are predicted to be in the top quintile and whose share allocated to the bank is predicted to be below average, the bank will be addressing 18% of its customer base that account for only 1% of the investment dollars already inside the bank but

FIGURE 2
Factor Loadings

A: Ownership and Total Decisions



B: Share and Total Decisions



48% of the investment dollars that are currently outside the bank.

Finally, consider the segmentation scheme that Figure 1 illustrates. Using estimated share of wallet and total wallet to segment its customer base, the bank can target the segment on the upper-left-hand corner—namely, those with total wallet in the top quintile and below-average share of wallet. Our approach based on Model C yields 13% of the validation sample customers for targeting. These predicted targets account for 51% of the validation sample's financial requirements that are currently served outside the focal bank. Again, this suggests substantial targeting efficiency (with a lift of 51%/13% = 3.9).

Concluding Remarks

Firms lack individual-level, industrywide customer data because they seldom have information about their customers' relationships with competitors. As a result, many CRM initiatives ignore customers' transactions with competing firms, which we believe reflects a tendency of enterprises taking the new customer-centric paradigm of marketing to an inward-looking extreme. We provide direct evidence that transaction levels inside a firm alone are largely uninformative with respect to a customer's transaction levels outside the firm. This highlights the risks of gauging a customer's potential value by relying solely on profitability recorded in the internal database. Both internal and external data are necessary to distinguish customers with large total market potential and small share from those with small total market potential and large share. Although these two types of customers are indistinguishable on the basis of internally recorded transactions alone, they call for different relationship development strategies.

In general, it is infeasible to obtain transaction records from competing firms, but firms can obtain external relationship data for a small sample of their customers through customer surveys or other secondary sources. We present a list augmentation approach that enables firms to combine internal records with these external data collected for a sample of customers to calibrate a predictive model that can then be used to estimate total and share of requirements for all customers in all categories. In our empirical illustration, we apply three such models to a proprietary data set provided by a major U.S. bank, containing information for more than 34,000 customers' holdings of financial products in ten categories both inside and outside the bank. These data enable us to test the performance of these models in imputing wallet size and share of wallet only on the basis of internal data. We demonstrate that firms can use our approach to segment customers on the basis of share of wallet and total wallet and to discriminate between high-share, small-wallet customers and low-share, large-wallet customers.

One of our three proposed models stands out in several ways: (1) the parsimony of the parameter space, (2) better performance in predicting the sizes of total and share variables and in targeting customers with large wallet but low share, and (3) the ease in interpreting the parameter estimates for behavioral insights (e.g., how customers' share decisions are correlated across product categories, how these decisions are correlated with total decisions and other customer characteristics). In addition, this model extends extant approaches for imputing data missing because of subsampling (Kamakura and Wedel 2000; Little and Rubin 2002; Schafer 1997) to the context in which multiple unobserved customer decisions—which categories to select, how much to expend in these categories, and how large a share for the focal vendor in each category—are simultaneously imputed from the observed joint outcomes of these decisions (i.e., how much, if any, to expend on the focal vendor's offerings).

Our study also leads to some notable behavioral findings on customers' share decisions. For example, we find that the bank under study has a smaller share of its higher-income customers' wallets. Thus, the bank may want to invest more in its high-income clientele to gain a larger share of their business. In addition, longer customer tenure is not necessarily associated with larger customer share, which runs counter to the conventional wisdom that the longer a customer stays with a company, the more he or she buys from the company. Related to tenure, another avenue for further exploration is to ascertain whether a decreasing share of wallet can be used as an early warning signal to prevent customer attrition, which inevitably entails examining longitudinal share-of-wallet movements. In general, we believe that variations in share of requirements across customers, product categories, and periods should prove to be a fertile ground for response modeling and for evaluating the impacts of different marketing instruments and competitive actions. Insights from these studies can be used to identify the lead indicators and drivers behind such variations, which can then be used to optimize allocation of marketing resources in CRM.

Although we illustrate our approach using data from a major consumer bank, caution should be exercised in extrapolating our specific findings to other institutions and industries. Nonetheless, the modeling framework we developed herein can be readily adapted to any industry in which consumers routinely fulfill their category requirements by purchasing various products/services simultaneously from multiple competing suppliers (e.g., retailing, direct marketing). We believe that share of category requirements can potentially play a more prominent role in improving the understanding and management of customer relationships in a broad range of industries, and our modeling framework could be viewed as a step toward achieving this goal by generating insights into customers' allocation of their business across vendors and by augmenting firms' customer databases with reasonably accurate estimates of total and share of category requirements for each individual customer.

Appendix A
Model Estimation

In Appendix A, we focus on the estimator for Model C. First, let $\lambda_{ijk} = \alpha_{jk} + x_i'\beta_{jk} + z_i'\gamma_{jk}$ for k = 1, 2, or 3. For all possible scenarios of T_{ij} and S_{ij}, we have the following densities conditional on z_i:

When $T_{ij} = 0$, $f(T_{ij}, S_{ij}) = f(\varepsilon_{ij1} \leq -\lambda_{ij1})$, or formally,

$$\text{(A1)} \qquad f(T_{ij}, S_{ij}|z_i; x_i, \Theta) = \Phi(-\lambda_{ij1}) \equiv \text{Prob}_{ij[1]}(z_i);$$

when $T_{ij} > 0$ and $S_{ij} = 1$, $f(T_{ij}, S_{ij}) = f[\varepsilon_{ij1} > -\lambda_{ij1}, \varepsilon_{ij2} = \ln(T_{ij}) - \lambda_{ij2}, \varepsilon_{ij3} \geq 1 - \lambda_{ij3}]$, or

$$\text{(A2)} \quad f(T_{ij}, S_{ij}|z_i; x_i, \Theta) = \Phi(\lambda_{ij1}) \times \frac{1}{\sigma_{j2}} \varphi\left[\frac{\ln(T_{ij}) - \lambda_{ij2}}{\sigma_{j2}}\right] \times \Phi\left(\frac{\lambda_{ij3} - 1}{\sigma_{j3}}\right) \equiv \text{Prob}_{ij[2]}(z_i);$$

when $T_{ij} > 0$ and $S_{ij} = 0$, $f(T_{ij}, S_{ij}) = f[\varepsilon_{ij1} > -\lambda_{ij1}, \varepsilon_{ij2} = \ln(T_{ij}) - \lambda_{ij2}, \varepsilon_{ij3} \leq -\lambda_{ij3}]$, or

$$\text{(A3)} \quad f(T_{ij}, S_{ij}|z_i; x_i, \Theta) = \Phi(\lambda_{ij1}) \times \frac{1}{\sigma_{j2}} \varphi\left[\frac{\ln(T_{ij}) - \lambda_{ij2}}{\sigma_{j2}}\right] \times \Phi\left(\frac{-\lambda_{ij3}}{\sigma_{j3}}\right) \equiv \text{Prob}_{ij[3]}(z_i); \text{ and}$$

when $T_{ij} > 0$ and $1 > S_{ij} > 0$, $f(T_{ij}, S_{ij}) = f[\varepsilon_{ij1} > -\lambda_{ij1}, \varepsilon_{ij2} = \ln(T_{ij}) - \lambda_{ij2}, \varepsilon_{ij3} = S_{ij} - \lambda_{ij3}]$, or

$$\text{(A4)} \quad f(T_{ij}, S_{ij}|z_i; x_i, \Theta) = \Phi(\lambda_{ij1}) \times \frac{1}{\sigma_{j2}} \varphi\left[\frac{\ln(T_{ij}) - \lambda_{ij2}}{\sigma_{j2}}\right] \times \frac{1}{\sigma_{j3}} \varphi\left(\frac{S_{ij} - \lambda_{ij3}}{\sigma_{j3}}\right) \equiv \text{Prob}_{ij[4]}(z_i).$$

The terms $\Phi(\cdot)$ and $\varphi(\cdot)$ represent cumulative and probability density functions of the standard normal distribution, respectively. Because z_i is unobservable from a modeler's perspective, we need to integrate it out when deriving the likelihood contribution of individual i:

$$\text{(A5)} \quad L_i = \int \prod_1 \text{Prob}_{ij[1]}(z_i) \prod_2 \text{Prob}_{ij[2]}(z_i) \prod_3 \text{Prob}_{ij[3]}(z_i) \prod_4 \text{Prob}_{ij[4]}(z_i) \prod_{p=1}^{P} \varphi(z_{ip})\, dz_{i1} \cdots dz_{iP},$$

where Π_1, Π_2, Π_3, and Π_4 denote the product over four different types of observations across all product categories; an observation belongs to Type 1 if $T_{ij} = 0$, Type 2 if $T_{ij} > 0$ and $S_{ij} = 1$, Type 3 if $T_{ij} > 0$ and $S_{ij} = 0$, and Type 4 if $T_{ij} > 0$ and $1 > S_{ij} > 0$.

For a given P, the dimensionality of the unobserved customer characteristics, we estimate Model C by maximizing the sample likelihood function, which is defined as the product of the individual likelihood functions in Equation A5 across all i's in the calibration subsample of I. We use simulation to evaluate the integrals, which gives rise to a simulated maximum likelihood estimator in which the individual likelihood contributions in Equation A5 can be approximated as

$$\text{(A6)} \qquad L_i \approx \frac{1}{R} \sum_{r=1}^{R} \prod_1 \text{Prob}_{ij[1]}(z_i^r) \prod_2 \text{Prob}_{ij[2]}(z_i^r) \prod_3 \text{Prob}_{ij[3]}(z_i^r) \prod_4 \text{Prob}_{ij[4]}(z_i^r),$$

where z_i^r is the rth draw from a P-dimensional multivariate standard normal distribution and R is the total number of draws taken. An appealing aspect of the simulated maximum likelihood estimator is that the simulated likelihood function in Equation A6 is twice differentiable, simplifying likelihood maximization with gradient-based search algorithms. We use a unique Halton sequence to simulate each dimension of z_i and assign a different set of draws to each customer. In determining the appropriate R, we adopt the following heuristic: For any given P, we begin with 50P draws and then double the number of draws until no significant improvements can be obtained in estimator efficiency (determined by comparing the standard errors of parameter estimates based on different numbers of draws, as well as the associated likelihoods).

This discussion indicates how our model can be estimated for a given P. To determine the number of factors, we use the BIC. More specifically, we begin with P = 1, then P = 2, and so on, until the resulting BIC stops decreasing.

Appendix B
Imputation Procedure

After calibrating Model C, we are interested in making inferences about the unobserved customer heterogeneities; that is, we impute z_i, the latent factor scores of each individual customer, by combining model parameter estimates and information available for individual i. Depending on the availability of information at the individual level, the formula for imputing z_i varies. We detail the imputation procedures for two scenarios of data availability.

In Scenario 1, both T_{ij} and S_{ij} are observed (or, equivalently, both Y_{ij}^1 and Y_{ij}^0 are observed). Recall that $\Pi_k \text{Prob}_{ij[k]}(z_i)$ for k = 1, 2, 3, or 4, as defined in Appendix A. We determine the marginal density function for T_{ij}, S_{ij}, and z_i as follows:

$$\begin{aligned} \text{(B1)} \quad & f(T_{i1}, S_{i1}, \ldots, T_{iJ}, S_{iJ}, z_i; x_i, \hat{\Theta}) \\ &= \prod_{j=1}^{J} f(T_{ij}, S_{ij}|z_i; x_i, \hat{\Theta}) \prod_{p=1}^{P} \varphi(z_{ip}) \\ &= \prod_1 \text{Prob}_{ij[1]}(z_i) \prod_2 \text{Prob}_{ij[2]}(z_i) \prod_3 \text{Prob}_{ij[3]}(z_i) \prod_4 \text{Prob}_{ij[4]}(z_i) \prod_{p=1}^{P} \varphi(z_{ip}) \equiv Q_i(z_i). \end{aligned}$$

Because T_{ij} and S_{ij} are observed, this density function can be calculated for any z_i, which enables us to impute customer i's latent factor scores by maximizing $Q_i(z_i)$ over z_i. Formally, $\widehat{Z_i}$ $(T_{i1}, S_{i1}, \ldots, T_{iJ}, S_{iJ}; x_i, \widehat{\Theta}) = \arg\max[Q_i(z_i)]$.

In Scenario 2, only Y^1_{ij} is observed, whereas T_{ij}, S_{ij}, and Y^0_{ij} are unobserved. Again, the marginal density function for Y^1_{ij} and z_i is

$$\text{(B2)}\quad f(Y^1_{i1}, \ldots, Y^1_{iJ}, z_i; x_i, \hat{\Theta}) = \prod_{j=1}^{J} f(Y^1_{ij}|z_i; x_i, \hat{\Theta}) \times \prod_{p=1}^{P} \varphi(Z_{ip}).$$

When $f(Y^1_{ij}|z_i; x_i, \hat{\Theta})$ is available for $\forall j$, $f(Y^1_{i1}, \ldots, Y^1_{iJ}, z_i; x_i, \hat{\Theta})$ is defined as

$$\text{(B3)}\quad \widehat{Z_i}(Y^1_{i1}, \ldots, Y^1_{iJ}, z_i; x_i, \hat{\Theta}) = \arg\max\left[f(Y^1_{i1}, \ldots, Y^1_{iJ}, z_i; x_i, \hat{\Theta})\right] = \arg\max\left[\prod_{j=1}^{J} f(Y^1_{ij}|z_i; x_i, \hat{\Theta}) \prod_{p=1}^{P} \varphi(Z_{ip})\right].$$

Thus, when only Y^1_{ij} is observed, the central task in imputing z_i is to calculate conditional density $f(Y^1_{ij}|z_i; x_i, \hat{\Theta})$. Depending on whether $Y^1_{ij} = 0$ or $Y^1_{ij} > 0$, different formulas are needed to calculate $f(Y^1_{ij}|z_i; x_i, \hat{\Theta})$. When $Y^1_{ij} = 0$, it can result from two kinds of situations: (1) $T_{ij} = 0$ or (2) $T_{ij} > 0$ and $S_{ij} = 0$. Formally, when $Y^1_{ij} = 0$,

$$\text{(B4)}\quad f(Y^1_{ij}|z_i; x_i, \hat{\Theta}) = f(T_{ij} = 0|z_i; x_i, \hat{\Theta}) + f(T_{ij} > 0, S_{ij} = 0|z_i; x_i, \hat{\Theta}) = \Phi(-\lambda_{ij1}) + \Phi(\lambda_{ij1}) \times \Phi\left(\frac{-\lambda_{ij3}}{\sigma_{j3}}\right) \equiv U_{ij[0]}(z_i),$$

where $\lambda_{ijk} \equiv \alpha_{jk} + x_i'\beta_{jk} + z_i'\gamma_{jk}$ for $k = 1, 2$, or 3.

When $Y^1_{ij} > 0$, it can also result from two kinds of situations: (1) $T_{ij} = Y^1_{ij}$ and $S_{ij} = 1$ or (2) $T_{ij} \times S_{ij} = Y^1_{ij}$ and $1 > S_{ij} > 0$. Formally, when $Y^1_{ij} > 0$,

$$\text{(B5)}\quad f(Y^1_{ij}|z_i; x_i, \hat{\Theta}) = f(T_{ij} = Y^1_{ij}, S_{ij} = 1|z_i; x_i, \hat{\Theta}) + f(T_{ij} \times S_{ij} = Y^1_{ij}, 1 > S_{ij} > 0|z_i; x_i, \hat{\Theta}) =$$

$$f(T_{ij} = Y^1_{ij}, S_{ij} = 1|z_i; x_i, \hat{\Theta}) + \int_{1>S>0} f\left(T_{ij} = \frac{Y^1_{ij}}{S}\Big|S_{ij} = S, z_i; x_i, \hat{\Theta}\right) f(S_{ij} = S|z_i; x_i, \hat{\Theta})dS =$$

$$\Phi(\lambda_{ij1}) \times \left\{\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln(Y^1_{ij}) - \lambda_{ij2}}{\sigma_{j2}}\right]\Phi\left(\frac{\lambda_{ij3} - 1}{\sigma_{j3}}\right) + \int_{1>S>0} \frac{1}{\sigma_{j2}} \varphi\left[\frac{\ln\left(\frac{Y^1_{ij}}{S}\right) - \lambda_{ij2}}{\sigma_{j2}}\right] \frac{1}{\sigma_{j3}}\varphi\left(\frac{S - \lambda_{ij3}}{\sigma_{j3}}\right)dS\right\} \equiv U_{ij[1]}(z_i).$$

Combining this, we obtain the following:

$$\text{(B6)}\quad f(Y^1_{i1}, \ldots, Y^1_{iJ}, z_i; x_i, \hat{\Theta}) = \prod_{j=1}^{J} f(Y^1_{ij}|z_i; x_i, \hat{\Theta})$$

$$\prod_{p=1}^{P} \varphi(Z_{ip}) = \prod_{0} U_{ij[0]}(z_i) \prod_{1} U_{ij[1]}(z_i) \prod_{p=1}^{P} \varphi(Z_{ip}) \equiv V_i(Z_i),$$

where Π_0 and Π_1 denote the product over two different types of observed Y^1_{ij} across all product categories; an observation belongs to Type I if $Y^1_{ij} = 0$ and to Type II if $Y^1_{ij} > 0$. To impute the latent factor scores when only Y^1_{ij} is observed, we can maximize $V_i(z_i)$ over z_i. Formally, $\widehat{Z_i}(Y^1_{i1}, \ldots, Y^1_{iJ}; x_i, \hat{\Theta}) = \arg\max[V_i(z_i)]$.

We now discuss the prediction of $\widehat{T_{ij}}$ and S_{ij}. Given $\widehat{\Theta}$, the estimated model parameters, and $\widehat{z_i}$, the imputed latent factor scores, we can predict T_{ij}, customer i's total category requirements, and S_{ij}, shares of category requirements that are served by the focal firm, conditional on (1) observed Y^1_{ij}, levels of category requirements that are served by the focal firm, and (2) x_i, observable customer characteristics. (Instead of plugging in $\widehat{z_i}$, an alternative is to integrate z_i out, which in practice leads to predictions that are of no significant differences but could take significantly more time to implement when the dimensionality of z_i is high.) The rest of this section demonstrates the formulas for making these predictions.

For categories in which $Y^1_{ij} = 0$, we can predict, for example, the expected value of T_{ij} conditional on $T_{ij} > 0$,

$$\text{(B7)}\quad E(T_{ij}|T_{ij} > 0, Y^1_{ij} = 0, \widehat{z_i}; x_i, \widehat{\Theta}) = \exp\left(\lambda_{ij2} + \frac{\sigma^2_{j2}}{2}\right),$$

and the expected value of S_{ij} conditional on $T_{ij} > 0$,

$$\text{(B8)}\quad E(S_{ij}|T_{ij} > 0, Y^1_{ij} = 0, \hat{z}_i; x_i, \widehat{\Theta}) = 0.$$

Similarly, for categories in which $Y^1_{ij} > 0$, we can make the foregoing as follows: The expected value of T_{ij} conditional on $T_{ij} > 0$ is

$$\text{(B9)}\quad E(T_{ij}|T_{ij} > 0, Y^1_{ij} = Y > 0, \hat{z}_i; x_i, \widehat{\Theta})$$

$$= \left\{\left(\frac{Y^1_{ij}}{1}\right)\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(Y^1_{ij}\right) - \lambda_{ij2}}{\sigma_{j2}}\right]\Phi\left(\frac{\lambda_{ij3} - 1}{\sigma_{j3}}\right) + \int_{1>S>0} \frac{Y^1_{ij}}{S}\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(\frac{Y^1_{ij}}{S}\right) - \lambda_{ij2}}{\sigma_{j2}}\right]\frac{1}{\sigma_{j3}} \varphi\left(\frac{S - \lambda_{ij3}}{\sigma_{j3}}\right)dS\right\} \Big/ \left\{\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(Y^1_{ij}\right) - \lambda_{ij2}}{\sigma_{j2}}\right]\right.$$

$$\Phi\left(\frac{\lambda_{ij3}-1}{\sigma_{j3}}\right)+\int_{1>S>0}\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(\frac{Y_{ij}^{1}}{S}\right)-\lambda_{ij2}}{\sigma_{j2}}\right]\frac{1}{\sigma_{j3}}\varphi\left(\frac{S-\lambda_{ij3}}{\sigma_{j3}}\right)dS\Bigg\},$$

and the expected value of S_{ij} conditional on $T_{ij} > 0$ is

$$\text{(B10)}\qquad E(S_{ij}|T_{ij}>0,\ Y_{ij}^{1}=Y>0,\ \hat{z}_{i};\ x_{i},\ \hat{\Theta})$$

$$=\Bigg\{1\times\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(Y_{ij}^{1}\right)-\lambda_{ij2}}{\sigma_{j2}}\right]\Phi\left(\frac{\lambda_{ij3}-1}{\sigma_{j3}}\right)$$

$$+\int_{1>S>0}S\times\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(\frac{Y_{ij}^{1}}{S}\right)-\lambda_{ij2}}{\sigma_{j2}}\right]\frac{1}{\sigma_{j3}}$$

$$\varphi\left(\frac{S-\lambda_{ij3}}{\sigma_{j3}}\right)dS\Bigg\}\Bigg/\Bigg\{\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(Y_{ij}^{1}\right)-\lambda_{ij2}}{\sigma_{j2}}\right]$$

$$\Phi\left(\frac{\lambda_{ij3}-1}{\sigma_{j3}}\right)+\int_{1>S>0}\frac{1}{\sigma_{j2}}\varphi\left[\frac{\ln\left(\frac{Y_{ij}^{1}}{S}\right)-\lambda_{ij2}}{\sigma_{j2}}\right]$$

$$\frac{1}{\sigma_{j3}}\varphi\left(\frac{S-\lambda_{ij3}}{\sigma_{j3}}\right)dS\Bigg\}.$$

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Rajkumar Venkatesan, V. Kumar, & Nalini Ravishanker

Multichannel Shopping: Causes and Consequences

The authors explore the drivers of multichannel shopping and the impact of multichannel shopping on customer profitability. Through a longitudinal analysis, the authors provide evidence that multichannel shopping is associated with higher customer profitability. Using the social exchange theory, they develop hypotheses regarding the impact of several customer–firm interaction characteristics on customer channel adoption duration. They propose a shared-frailty hazard model for testing the proposed hypotheses. They use the customer database of an apparel manufacturer that sells through three distinct channels for the empirical analysis and find that frequency-related interaction characteristics have the greatest influence on second-channel adoption duration. In contrast, proportion of returns, a purchase-related interaction characteristic, has the greatest influence on third-channel adoption duration. Variation across customers in purchase-related attributes has a greater impact on the duration to adopt the second channel than the duration to adopt the third channel. In contrast, variation across customers in the channel-related attributes has a greater impact on the third-channel adoption duration than on the second-channel adoption duration. The customer–firm interaction characteristics identified in this study and the proposed model framework allow for forward-looking allocation of multichannel marketing resources.

Maintaining multiple channels of transaction with a customer is considered essential for sustained growth in the current competitive environment (Wind and Mahajan 2002). Our study investigates three critical aspects of the customer–firm relationship in a multichannel environment. First, many retailers employ various strategies that are designed to encourage customers to shop in multiple channels. For example, PetSmart prints $10 coupons on store receipts that are valid only for online purchases (Sandsmark 2001). To a large extent, the retailer's attempts to encourage customers to shop in multiple channels are based on the belief that multichannel customers have a higher annual purchase volume than single-channel customers (e.g., DoubleClick 2004; Jupiter Research 2005). Thus far, and on the basis of a cross-sectional analysis of the total profits provided by multichannel versus single-channel customers, academic research has found that multichannel shoppers are significantly more profitable than single-channel shoppers (Kumar and Venkatesan 2005; Thomas and Sullivan 2005). However, a cross-sectional analysis precludes researchers from understanding whether profitable customers tend to shop in multiple channels and whether shopping in multiple channels leads to higher customer profits. Extending previous findings, we use longitudinal information on customer transactions with a firm that is typically available in customer relationship management (CRM) databases to explore whether shopping in multiple channels increases customer profits.

Second, predicting the time a customer takes to adopt an additional channel (i.e., channel adoption duration) would help multichannel retailers in various resource allocation decisions. The focus on marketing accountability has spurred the allocation of marketing resources at each business cycle (e.g., quarters) to individual customers, products, and channels to maximize return on marketing investments (Rust, Lemon, and Zeithaml 2004). If multichannel shopping leads to higher profits and given that marketing communications have a positive influence on customer channel choice (Kumar and Venkatesan 2005; Thomas and Sullivan 2005), predicting customer channel adoption duration would help managers further refine their resource allocation decisions at each quarter by prioritizing channel adoption campaigns among the profitable customers to those who are likely to adopt a new channel in that quarter. For example, PetSmart can expect better returns by providing coupons to customers who are likely to start shopping online. Even if a firm decides not to encourage multichannel shopping proactively, predicting channel adoption duration would enable a firm to obtain a better understanding of the level of resources required in each channel. For example, predicting when offline-only customers would adopt an online channel would help a "bricks-and-click" retailer better forecast the progress in the level of online orders and correspondingly plan the level of resources (e.g., inventory) that would be required to fulfill the online orders satisfactorily.

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Third, we attempt to develop a theoretical basis for the identification of the customer–firm interaction factors so that the proposed framework is sufficiently generalizable across various contexts. Therefore, we propose a conceptual framework that explores the impact of customer–firm interaction characteristics on channel adoption duration.

To summarize, the objectives of our study are as follows:

- To explore the influence of multichannel shopping on customer profitability,
- To provide a conceptual framework for evaluating the influence of customer–firm interactions on customer channel adoption duration, and
- To develop a model formulation for empirically testing the proposed conceptual framework and predicting customer channel adoption duration.

We use the customer database of a large apparel manufacturer that provides three channels for transactions: full-price bricks-and-mortar stores, discount bricks-and-mortar stores, and a Web site. In the next section, we perform an exploratory data analysis to investigate whether multichannel shopping leads to increased customer profitability.

Exploring the Impact of Multichannel Shopping on Customer Profits

In this section, we use a cohort of customers who made their first purchase from the apparel retailer during April 2000, and we observe their transactions until October 2003. All three channels were available to the customers during the observation window.

Longitudinal Analysis[1]

Our intuition for understanding the impact of multichannel shopping on customer profits is to track customer profits each year and to explore whether profits are higher in years when customers engage in multichannel shopping, after we account for (1) any general time trends, (2) purchase activity, and (3) customer-specific variation in profits due to omitted variables.[2] In each year (t), we calculate the total profits from customer i (Profit_{it}) and create a binary (1/0) indicator of multichannel shopping (Multi_Ind_{it}). The Multi_Ind_{it} measure can be confounded by transaction activity when customers make only a single transaction in a year. Because we observed that some customers made only one transaction in a year, we conducted our analyses only on customers who had at least two transactions in each year. This represents a conservative setting for observing the influence of multichannel shopping on profits because each customer included in the analysis has an opportunity to shop in multiple channels.

Partial regression plots and extra sum-of-squares F-tests are useful in multiple linear regression analysis to quantify whether a variable had additional significance in explaining the predictor variable in a model with a basket of possibly correlated predictors (Ravishanker and Dey 2001). In our context, this structure is useful for understanding whether a single predictor variable (in our case, Multi_Ind_{it}) is a useful addition to a model for explaining customer profits when Multi_Ind_{it} is probably correlated with preexisting covariates in the model, such as purchase activity.[3] In other words, the partial regression plots would enable us to disentangle the effects of multichannel shopping and purchase activity on customer profits. We randomly sampled 8882 customers from the cohort for our analysis.

Step 1

We model profits as a linear function of (1) t, or time index in years (i.e., t = 1 for the first year, and so forth); (2) Tran_{it}, or the number of transactions that customer i makes in time t (i.e., purchase activity), (3) lagged profits (Profit_{it-1}), and (4) lagged multichannel shopping (Multi_Ind_{it-1}):

$$(1)\quad \text{Profit}_{it} = \gamma_{1,0} + \gamma_{1,1} \times t + \gamma_{1,2} \times \text{Tran}_{it} + \gamma_{1,3} \times \text{Profit}_{it-1} + \gamma_{1,4} \times \text{Multi\_Ind}_{it-1} + \varepsilon 1_{it}.$$

We allow for potential correlation in profits from the same customer over years through the error term, $\varepsilon 1_{it}$. Let the vector $\varepsilon 1_i = (\varepsilon 1_{i1}, \ldots, \varepsilon 1_{i4})'$ represent the error terms that correspond to customer i over the four years in our analysis. We assume that $\varepsilon 1_i$ follows a multivariate normal distribution with zero mean and variance–covariance matrix $V1_i$. The off-diagonal elements of $V1_i$, $\alpha 1_{jk}$ ($j \neq k$), capture the correlation in profits across years for a single customer. We use a generalized linear model (GLIM) formulation to estimate the parameters in Equation 1 (i.e., we use Proc Genmod in SAS with normal distribution, an identity link function, and the repeated option) and obtain the Pearson residuals ($\hat{\varepsilon} 1_{it}$). The results from estimating Equation 1 appear in Table 1, Panel A.

As we expected, the estimates in Table 1, Panel A, indicate that time index (coefficient of t = 50.6), purchase activity (coefficient of Tran_{it} = 12.5), lagged profits (coefficient of Profit_{it-1} = .03), and lagged indicator of multichannel shopping (coefficient of Multi_Ind_{it-1} = 15.8) have a positive, significant influence on profits.

Step 2

For each customer i, we assume that the various binary indicators of multichannel shopping (Multi_Ind_{it}) are correlated Bernoulli random variables with parameter p_{it}. We model the logit transformation of p_{it} as a linear function of the same independent variables in Equation 2 (i.e., t, Tran_{it}, Profit_{it-1}, and Multi_Ind_{it-1}:

$$(2)\quad \text{logit}(p_{it}) = \gamma_{2,0} + \gamma_{2,1} \times t + \gamma_{2,2} \times \text{Tran}_{it} + \gamma_{2,3} \times \text{Profit}_{it-1} + \gamma_{2,4} \times \text{Multi\_Ind}_{it-1}.$$

---

[1] We replicated the cross-sectional analysis in Kumar and Venkatesan (2005) and Thomas and Sullivan (2005) and obtained similar results.

[2] We also replicated the analysis with quarterly and semiannual data, and the substantive conclusions do not change with the level of data aggregation. For interested readers, the results are available on request.

[3] The partial regression analysis satisfies the condition that Cox (1992, p. 293) proposes for statistical causality—namely "a variable x_c is a cause of y_E if it occurs in all regression equations for y_E irrespective of the other variables x_b that are included."

TABLE 1
Longitudinal Analysis of Consequences of Multichannel Shopping

A: Longitudinal Customer Profitability Model

Dependent Variable = $Profit_{it}$*

Independent Variables	Coefficient
Intercept	3.9
Time (t)	67.9
$Tran_{it}$	7.6
$Profit_{it-1}$	.03
$Multi\_Ind_{it-1}$	15.8

B: Longitudinal Multichannel Shopping Model

Dependent Variable = $Multi\_Ind_{it}$*

Independent Variables	Coefficient
Intercept	−1.4
Time (t)	.1
$Tran_{it}$	.02
$Profit_{it-1}$	.01
$Multi\_Ind_{it-1}$	1.2

C: Impact of Multichannel Shopping on Customer Profitability

Dependent Variable = $\hat{\varepsilon}1_{it}$

Independent Variables	Coefficient
Intercept	.01
$\hat{\varepsilon}2_{it}$	33.1*

*Significant at $\alpha < .01$.

We model the correlation in p_{it} over years for customer i similar to $V1_i$ in Equation 1. We use a GLIM formulation to estimate the parameters in Equation 2 (i.e., using Proc Genmod in SAS with Bernoulli distribution, a logit link function, and the repeated option) and obtain the Pearson residuals ($\hat{\varepsilon}2_{it}$). The results from estimating Equation 2 appear in Table 1, Panel B.

The GLIM formulation for Equations 1 and 2 is equivalent to a linear regression and a logistic regression, respectively. However, the GLIM formulation enables us to estimate the residuals ($\varepsilon 2_{it}$) in Equation 2 (which is essential for Step 3), something that is not possible in a logistic regression formulation. The significant influence of time index (coefficient of t = .4), purchase activity (coefficient of $Tran_{it} = .10$), lagged profits (coefficient of $Profit_{it-1} = .01$), and lagged indicator of multichannel shopping (coefficient of $Multi\_Ind_{it-1} = 1.2$) provides justification for using a partial regression plot.

Step 3

Finally, we run a regression of $\hat{\varepsilon}1_{it}$ (residuals from a regression of profits on the predictors, including purchase activity) on $\hat{\varepsilon}2_{it}$ (residuals from a regression of multichannel shopping on the predictors, including purchase activity):

$$\hat{\varepsilon}1_{it} = \gamma_{3,0} + \gamma_{3,1} \times \hat{\varepsilon}2_{it} + \varepsilon 3_{it}. \quad (3)$$

We use the GLIM formulation similar to Equation 1 to estimate Equation 3. The results appear in Table 1, Panel C.

From Table 1, Panel C, we observe that $\hat{\varepsilon}2_{it}$ has a positive, significant influence on $\hat{\varepsilon}1_{it}$ (.10), and the intercept is not significant. In other words, a plot of $\hat{\varepsilon}1_{it}$ versus $\hat{\varepsilon}2_{it}$ has a positive slope and crosses the origin. This indicates that multichannel shopping has a positive effect on customer profits, even after we remove the effect of other potential confounding variables, such as purchase activity, on both the profits and multichannel shopping. Similar to previous research, the results from estimating Equation 2 show that customers who are more profitable are also more likely to shop in multiple channels (Neslin et al. 2006).[4] In addition, the estimates of Equation 3 indicate that there is a positive reinforcement effect of multichannel shopping on customer profits beyond that of other factors, such as purchase activity. We also estimated Equation 1 with $Multi\_Ind_{it}$ as an additional independent variable. A likelihood-ratio test indicated strong support ($\lambda = .0032$, $\alpha < .01$) for a profit model that includes $Multi\_Ind_{it}$ as an independent variable relative to Equation 1, which does not include $Multi\_Ind_{it}$ as an independent variable.

Conceptual Framework

Fournier (1998) proposes that the everyday marketing-mix decisions constitute a set of behaviors enacted on behalf of the brand and form the cornerstone for considering the relationships between customers and brands (or firms), similar to interpersonal relationships between two human beings. Under this assumption, the social exchange theory of interpersonal relationships is applicable for studying channel adoption duration. According to social exchange theory, the interactions between people form the basis for the development of their relationship. People form and maintain a relationship as long as they believe and subsequently find it in their mutual interest to do so (Burgess and Huston 1979). The relationships are assumed to grow, develop, deteriorate, and dissolve as a consequence of the social exchange process (i.e., the interactions). Interacting in a widening array of settings (i.e., transacting across multiple channels) is considered one of the several behavioral consequences of relationship development (Berscheid, Snyder, and Omoto 1989; Burgess and Huston 1979).

Although several behavioral and psychological (or perceptual/subjective) aspects can determine the rate of relationship development (Hinde 1995) and channel adoption duration, we are interested in exploring only the impact of behavioral factors that are easily evident from CRM databases. We view the various purchase occasions and the communications from the firm to the customer as the interactions between partners in a relationship. The differences in interaction characteristics across customers affect the rate of relationship development and therefore explain the variation in the channel adoption duration. In addition to the interaction characteristics, individual differences, or observed customer heterogeneity, are expected to affect the rate of relationship development (Hays 1985) and, therefore, channel adoption duration. Figure 1 summarizes the proposed interaction characteristics and their expected effects on customer channel adoption duration. We classify interaction characteristics into purchase-related attributes, channel-related attributes, and frequency-related attributes.

---

[4] Note that a pure causal effect of multichannel shopping on customer profitability can be assessed only through a field experiment.

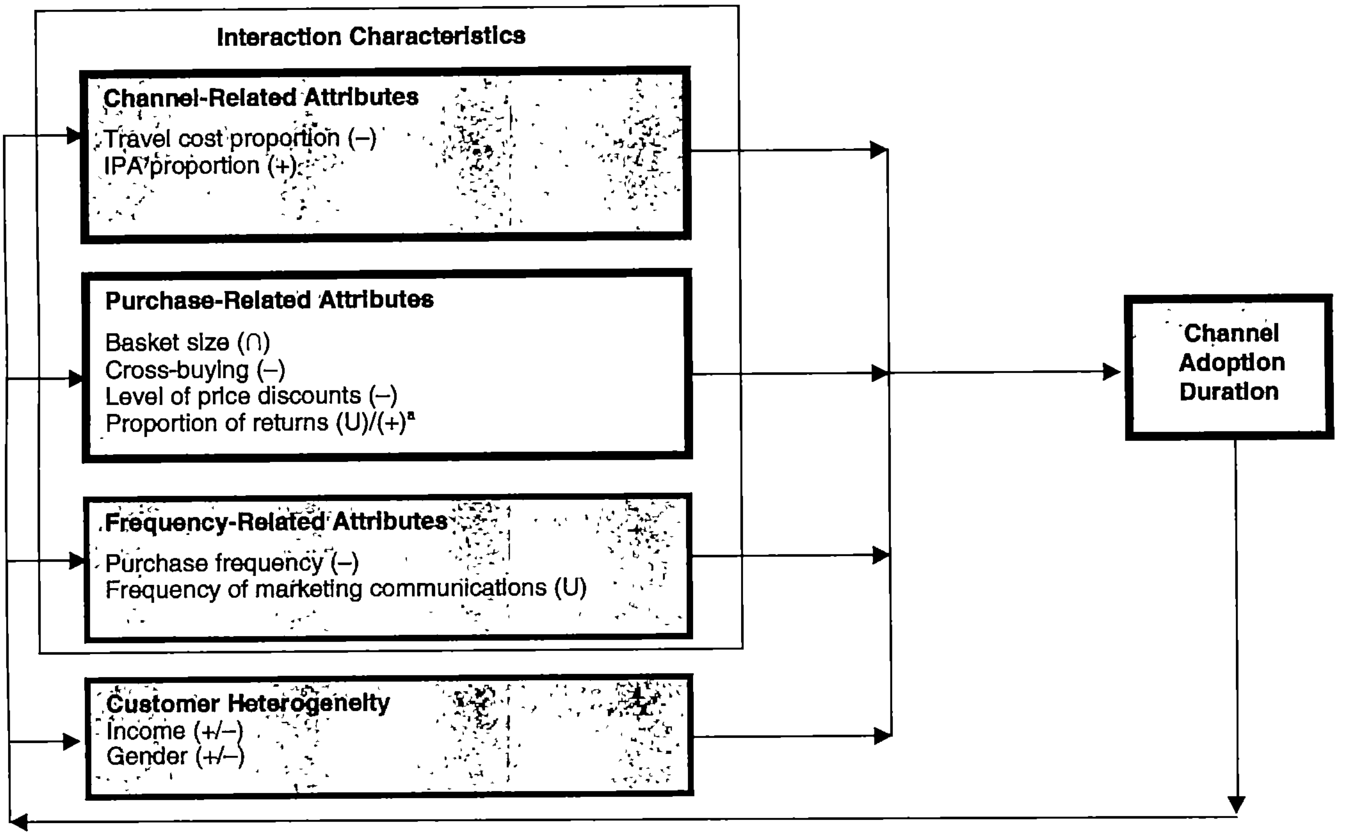
Interaction Characteristics: Purchase-Related Attributes

Basket size. Basket size is defined as the total quantity of items a customer purchases in a single shopping trip (Bell, Ho, and Tang 1998). It could be inferred that the larger the basket size (i.e., more products purchased in a transaction), the higher the utility provided by each interaction. In general, customers with smaller basket sizes (fill-in trips) are expected to pay higher prices because they have an immediate, unplanned consumption need that must be fulfilled. To the extent that the firm's products satisfy customers' immediate needs, customers who have smaller basket sizes are expected to derive higher utility from each interaction. It can be expected that customers who have very large basket sizes (planned trips) with a particular firm are satisfied with the firm's offerings because they are making consistent, planned visits and are purchasing large quantities.

Previous research has found that customers with intermediate basket sizes pay the lowest prices and purchase more items that are on feature and display (Mazumdar and Papatla 1995), implying that these customers are more focused on lower prices than on developing a relationship with the firm. Therefore, we propose that each interaction contributes more to relationship development for customers who have very small and very large baskets than for customers who have intermediate basket sizes. Given an equal number of interactions, relationship development is faster (and therefore channel adoption duration is shorter) for customers with either very small or very large basket sizes than for customers with intermediate basket sizes. Thus:

> H_1: There is an inverted U-shaped relationship between an increase in basket size and channel adoption duration.

FIGURE 1
Conceptual Model of Drivers of Channel Adoption Duration


Interaction Characteristics
Channel-Related Attributes
Travel cost proportion (–)
IPA proportion (+)
Purchase-Related Attributes
Basket size (∩)
Cross-buying (–)
Level of price discounts (–)
Proportion of returns (U)/(+)[a]
Frequency-Related Attributes
Purchase frequency (–)
Frequency of marketing communications (U)
Customer Heterogeneity
Income (+/–)
Gender (+/–)
Channel Adoption Duration

[a]The positive sign is for the third-channel adoption
Notes: IPA = immediate product availability.

Cross-buying. We define cross-buying as the number of different product categories a customer purchases from in a single shopping trip. Although the degree of cross-buying is associated with variation in customer demographics (Kamakura, Ramaswami, and Srivastava 1991), cross-buying is also found to be associated with customer satisfaction, after variation in customer demographics are controlled for. Specifically, for longer duration customers, a higher level of satisfaction with a firm's products leads to an increase in cross-buying, and regardless of relationship duration, lower satisfaction leads to a decrease in cross-buying (Verhoef, Frances, and Hoekstra 2001). In turn, customer satisfaction has been found to be positively associated with relationship duration and relationship development (Bolton 1998). Given an equal number of interactions, customers who have a higher degree of cross-buying are expected to develop greater familiarity (Kumar and Venkatesan 2005) and maintain their levels of satisfaction with a firm's products at each interaction. Thus:

> H_2: The higher the level of cross-buying, the shorter is the channel adoption duration.

Level of price discounts. Customers perceive a price discount on a product as a gain because the price they pay for the discounted product is less than their reference price for the product (Kalyanaram and Winer 1995). The availability of a discount can lead to relationship development because of the potential for savings the discount provides to the customer. This implies that relationship development is faster for customers who take advantage of the discounts presented to them. However, some customers may obtain a higher level of price discounts than others because they actively seek lower prices. These customers would be motivated to scan channels to obtain lower prices and thus would be associated with shorter channel adoption duration. Thus:

> H_3: The higher the level of price discounts a customer obtains, the shorter is the channel adoption duration.

Proportion of returns. We define proportion of returns as the ratio of the number of returns to the number of products a customer purchases. Product returns represent an instance in which customers explicitly express their dissatisfaction with the firm and can be perceived as bargaining efforts on the part of customers for better coordination of their interactions (Dwyer, Schurr, and Oh 1987). Studies that explore product returns from the customers' perspectives (rather than from the firm's perspective) find that when customers attribute the blame for product returns to themselves rather than to the firm, a product return can lead to higher repeat purchase and relationship development (Bower and Maxham 2006).

If firms treat customers who return products satisfactorily and make every effort to solve their problems, these customers can become loyal and exhibit positive word-of-mouth behavior (Reicheld 1998). Therefore, a customer's initial product returns are critical because they have the potential to strengthen the customer–firm relationship. However, a firm's failure to solve the customer's problem results in a persistence of return behavior, leading to the dissolution of the relationship or slowing the rate of relationship development (or longer channel adoption duration). Previous research has found that the influence of returns on customer purchase behavior is nonlinear (Venkatesan and Kumar 2004). Specifically, if the increase in returns exceeds a certain threshold, a customer may be more inclined to dissolve his or her relationship with a firm. Therefore, among single-channel shoppers, customers who have either a low or a high proportion of returns have a longer duration to adopt a second channel than customers who return products at moderate levels.

A customer is expected to exhibit a higher proportion of returns even when shopping in two channels if the firm had not satisfactorily managed his or her previous (probably when shopping in a single channel) product return occasions. Thus:

> H_{4a}: There is a U-shaped relationship between the proportion of returns when a customer shops in a single channel and the duration for the customer to adopt a second channel.
>
> H_{4b}: The higher the proportion of returns when a customer shops in two channels, the longer is the duration for the customer to adopt a third channel.

Interaction Characteristics: Frequency-Related Attributes

Purchase frequency. Customers who have a higher frequency of purchases are expected to develop familiarity with the products and transaction channels the firm provides at a faster rate than those who seldom purchase. Morgan and Hunt (1994) argue that to the extent that the interactions are satisfactory, frequent interactions might increase trust (in other words, reduce perceived risk) at a faster rate. Although quality of interaction is more important than frequency in determining the development of a relationship, an increase in the frequency of interactions also allows customers to increase the rate at which they form impressions of the firm's products and the benefits of interacting with the firm (Hinde 1979). Thus:

> H_5: The higher the purchase frequency, the shorter is the channel adoption duration.

Frequency of marketing communications. Marketing communications are critical in influencing customers' channel choices (Ansari, Mela, and Neslin 2005; Thomas and Sullivan 2005). Suppliers can use their contact strategy in one channel to motivate customers to migrate to other channels. However, the influence of marketing communications on customer behavior is nonlinear in nature (Fournier, Dobscha, and Mick 1997; Reinartz, Thomas, and Kumar 2005; Venkatesan and Kumar 2004). Up to a certain threshold, customers perceive higher levels of marketing communications as reciprocal communications from the firm with the intention of developing a mutually beneficial relationship. However, an increase in the level of marketing communications beyond this threshold can have dysfunctional consequences (Fournier, Dobscha, and Mick 1997) because customers begin to perceive the firm as not understanding their needs and simply pushing its products. This implies that relationship development is slower for customers who receive either very low levels or very high levels of marketing communications than for customers who receive an intermediate (or optimal) level of marketing communications. Thus:

> H_6: There is a U-shaped relationship between frequency of marketing communications and the channel adoption duration.

Interaction Characteristics: Channel-Related Attributes

The various channels differ on several factors, including time between ordering and receiving a product, richness of information presented, and accessibility/convenience (Ward 2001). Remote channels, such as Web sites and mail-order catalogs, are characterized by no traveling cost, and they can be used to order products at any time of the day, leading to greater accessibility/convenience. However, in these channels, there is a larger time difference between ordering and receiving a product, and the products cannot be physically examined, which leads to less product information than is the case for bricks-and-mortar stores. Conversely, the offline channels are characterized by no time difference between ordering and receiving the product as well as richer information about the product. However, these channels also have a nonzero traveling cost and are accessible only during the day. Therefore, we measure channel-related interaction attributes through (1) travel cost proportion and (2) immediate product availability (IPA) proportion.

Travel cost proportion. A customer's travel cost for a channel is defined as the distance between the customer's residence and the closest store in that channel. The travel cost proportion for a customer is measured as the ratio of the sum of the travel costs for all the channels the customer currently adopts to the sum of the travel costs of all the channels the firm provides. Typically, it is assumed that the travel cost for the online channel and the mail-order channel is zero.

In the context of packaged goods, studies have found that customers choose to shop in stores that are associated with lower travel cost (Bell, Ho, and Tang 1998). Given equal levels of relationship development, customers who are currently shopping in a channel that has a larger travel cost than other channels offered by a firm have a greater scope for reducing their travel cost by shopping in the firm's other channels. The incentive for customers to reduce their travel cost proportion and the greater scope for such reduction for customers who currently have a higher travel cost proportion are reflected in them having a shorter channel adoption duration. Thus:

> H_7: The higher the travel cost proportion in the current channels, the shorter is the channel adoption duration.

IPA proportion. A channel provides IPA if a customer is able to consume the product immediately after purchase. Channels that do not have IPA cannot provide customers with a rich interaction/experience with the product. For example, both the online channel and the mail-order catalogs do not have IPA and cannot provide a rich interaction experience with the product. Bricks-and-mortar stores provide customers with a rich interaction with the product, and the customers can also consume the product immediately in these channels, so a bricks-and-mortar store would have IPA.

Immediate product availability measures the costs related to both the time lag between product purchase and consumption and the nonavailability of the hedonic pleasure of the shopping process itself. The existence of IPA in a particular channel decreases the cost of transacting in that channel. We measure IPA proportion as the ratio of the number of channels that have IPA among a customer's current transaction channels to the number of channels that have IPA among all the channels the firm offers. Given that customers prefer to maximize the total utility of their shopping experience (Bell, Ho, and Tang 1998), we expect that customers who have a lower IPA proportion will be associated with shorter channel adoption duration. Thus:

> H_8: The higher the IPA proportion in the customer's current channels, the longer is the channel adoption duration.

Observed Customer Heterogeneity

Given previous findings of significant heterogeneity in channel migration behavior (Thomas and Sullivan 2005), it is important to include elements of observed customer heterogeneity in our framework. Sociodemographic variables, such as income and gender, have been found to affect customer store choice (Popkowski-Leszcyc and Timmermans 1997), channel choice (Inman, Shankar, and Ferraro 2004), and profitable lifetime duration (Reinartz and Kumar 2003).[5] Because of the lack of a convincing theory about gender and income effects on store and channel choice, we do not formulate a formal hypothesis, but we include gender in our model as a control variable.

Model

In our data, we observe the date and channel for each customer transaction. By definition, the time when a customer makes his or her first purchase in a second channel (T_2) is later than the time when a customer first transacts with the firm in any channel (T_1), and the time a customer makes his or her first purchase in a third channel (T_3) is later than T_2 (i.e., $T_3 > T_2 > T_1$). We study the impact of interaction factors on the duration it takes for a customer to adopt a second channel ($t_2 = T_2 - T_1$) and the duration it takes for a customer to adopt a third channel ($t_3 = T_3 - T_2$). When operationalized as such, the durations for adoption of the second and third channel (t_2 and t_3) are not ordered in time (i.e., t_3 can be greater or less than t_2) and are similar to interpurchase times, which are used widely in the literature (Jain and Vilcassim 1991). However, we also expect that the duration to adopt the third channel (t_3) is dependent on the duration to adopt the second channel (t_2). Given this expectation of dependence, multispell hazard models used to model customer interpurchase times are inappropriate because they assume that multiple events (i.e., the durations to adopt the second and third channels) are independent.

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[5] Although several other demographic factors could affect channel adoption duration, we use gender and income because only these demographic factors have reliable information (i.e., no missing values) in the customer database used in this study.

We model the duration to adopt a channel using a shared-frailty model framework (Hougaard 2000), which assumes that the second-channel adoption duration (t_2) and the third-channel adoption duration (t_3) are independent, given a common unobserved risk factor (w_i) that is specific to each individual i. Under this framework, the instantaneous probability (also called the customer's "hazard function") that customer i will adopt the jth channel (i.e., the second or third channel) follows the modified proportional hazards form:

$$\text{(4)}\quad h(t_{ij}, X_{ij}^*) = \frac{\left[F(t_{ij}) - F(t_{ij} - \Delta)\right]}{1 - F(t_{ij})} = h_0(t_{ij}) \times \psi(X_{ij}^*, \beta) \times w_i,$$

where Δ is the level of aggregation used in the analysis. For example, in our analysis, we measure t_{ij} in number of days, so Δ represents a day. For customer i, t_{ij} denotes the observed value of the random time to adopt the jth channel, $h(t_{ij}, X_{ij}^*)$ represents the corresponding hazard function (i.e., the instantaneous probability of adopting the jth channel at time t_{ij} given no adoption until time t_{ij}), $h_0(t_{ij})$ represents the baseline hazard, X_{ij}^* denotes the antecedents of channel adoption duration, $\psi(X_{ij}^*, \beta)$ represents the influence of the antecedents on the hazard of channel adoption, and w_i is the customer-specific frailty or the common risk factor. The observed durations t_2 and t_3 are independently conditional on w_i. In this model, the baseline hazard represents the probability distribution that characterizes a customer's channel adoption durations, and $\psi(X_{ij}^*, \beta)$ shifts the hazard up or down. We assume a Weibull baseline hazard for the time until the jth channel adoption:

$$\text{(5)}\quad h_0(t_{ij}) = \lambda_j \gamma t_{ij}{}^{\gamma - 1},$$

where γ (>0) is the shape parameter common to both second- and third-channel adoption duration[6] and λ_j (>0) is the adoption-specific scale parameter that allows the baseline hazard to vary between the second- and the third-channel adoption durations. We vary only the scale parameter to ensure identification of model parameters. The formulation for the baseline hazard as two Weibull distributions with a common shape and different scale parameters is similar to the bivariate Burr distribution (Hougaard 2000, p. 235). We use the following functional form to represent the covariate function:

$$\text{(6)}\quad \psi(X_{ij}^*, \beta) = e^{\beta_0' X_{i0}} \times e^{\beta_2' X_{i2} \varphi_2} \times e^{\beta_3' X_{i3} \varphi_3},$$

where

X_{i0} = a row vector of customer heterogeneity variables that are constant over the j channel adoption events,

X_{ij} = a row vector of interaction factors associated with the customer's transaction history when shopping in one channel for j = 2 and the customer's transaction history when shopping in two channels versus one channel for j = 3,

φ_j = 1 if the observation represents the jth channel adoption and 0 if otherwise,

β_0 = a row vector of coefficients for customer heterogeneity variables, and

β_j = a row vector of event-specific (i.e., adoption-specific) coefficients for the interaction factors.

We estimate a separate set of coefficients for the second- and third-channel coefficients to accommodate for any differences in customer behavior when shopping in a single channel (used to predict second-channel adoption duration) and when shopping in two channels (used to predict third-channel adoption duration). For each customer i, we model the shared frailty, w_i, as a random draw from a gamma distribution, such that scale and shape parameters are equal to each other (the mean of the gamma distribution is equal to one).[7] We impose this restriction to ensure identification of the model parameters (Hougaard 2000). The gamma distribution is represented as

$$\text{(7)}\quad w_i \sim \frac{w_i^{\kappa - 1} e^{-\kappa w_i} \kappa^\kappa}{\Gamma(\kappa)},$$

where κ (>0) represents both the scale and the shape parameters. For the duration to adopt a second channel, we calculate the interaction characteristics on the basis of a customer's transaction history when shopping in a single channel. Likewise, for the duration to adopt a third channel, we calculate the interaction characteristics on the basis of a customer's transaction history when shopping in two channels. In the analysis of channel adoption duration, we do not include the customer transactions that are observed after the customers adopt the third channel (i.e., only the first transaction in the third channel), because in this study, we focus only on the time they take to make their first transaction in the new channel. Calculating the interaction characteristics on the basis of customers' transactions before they adopt a new channel enables us to control for the possibility of endogeneity of the drivers of channel adoption. The likelihood function for our model framework is

$$\text{(8)}\quad L = \prod_{i=1}^{n} \prod_{j=2}^{3} \Big[(\lambda_j \gamma t_{ij}^{\gamma - 1} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2} \varphi_2 + \beta_3' X_{i3} \varphi_3})^{\delta_{ij}}$$

$$\times \exp(-\lambda_j t_{ij}^{\gamma} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2} \varphi_2 + \beta_3' X_{i3} \varphi_3}) \Big]^{\varepsilon_{ij}}.$$

The index, i, represents a customer, and the index, j, represents channel adoption (i.e., j = 2 represents the time until adoption of the second channel, and j = 3 represents the time until adoption of the third channel). The censoring indicator, δ_{ij}, is equal to 1 if the customer adopts the jth channel within the analyses time frame and 0 if the customer's adoption of the jth channel is not observed in data (i.e., if the duration for the jth channel adoption is censored). The product of the first (the hazard function) and second (the survival function) terms in the likelihood function provides the density function for the duration model. For uncensored observations, both the first and the second terms in the likelihood function (i.e., the density function) are applicable, and for censored observations, only the second term (i.e., the survivor function) is applicable. For single-channel shoppers, the duration to adopt the second channel is censored (i.e., $\delta_{i2} = 0$), and the duration to adopt the third channel is not applicable for these customers. Therefore, we set g_{i2} equal to one and g_{i3} equal to zero for these customers. In other words, only the censored duration to adopt the second channel contributes to the likelihood function for single-channel customers. For multichannel customers—that is, for both two-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 0$) and three-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 1$) customers—we set g_{i2} and g_{i3} equal to one.

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[6] We also plotted a histogram of duration for channel adoption across customers and found that a Weibull distribution represents the data best. Compared with the other distributions, the Weibull distribution provided the best fit to the data on the basis of the Anderson–Darling tests.

[7] The gamma distribution is the most commonly used distribution to model the frailty parameter (Hougaard 2000).

The estimation of Equation 8 using a maximum likelihood–based approach would require integration of the likelihood with respect to w_i (Hougaard 2000). As the Appendix shows, in Markov chain Monte Carlo (MCMC) methods, the model parameters are simulated directly from their posterior distributions, thus avoiding the need to integrate the likelihood over the frailty distribution. We complete the model specification by specifying prior distributions for the model parameters. We assume gamma distributed priors for λ_1, λ_2, γ, and κ and multivariate normal distributions priors for the response coefficients β_0, β_2, and β_3 (for further details on the prior distributions and the estimation methodology, see the Appendix).

Data

We use the transaction history of customers since their first purchase until the end of 2003 for our analyses.[8] The different modes of communication that the firm in this study uses include direct mail and e-mail. All the customers in our population made at least one purchase in the full-price bricks-and-mortar store, 92% made at least one purchase in the discount bricks-and-mortar store, and 55% made at least one purchase from the Web site. Similarly, 65% of the transactions occurred in the full-price bricks-and-mortar store, 26% of the transactions occurred in the discount bricks-and-mortar store, and 9% of the transactions occurred at the Web site. Whenever discounts are offered, on average, the full-price bricks-and-mortar stores offer a 25% discount, the discount bricks-and-mortar stores offer a 35% discount, and the Web site offers a 30% discount. On average, customers obtain discounts on 12% of their purchases from the full-price bricks-and-mortar stores, on 18% of their purchases from the discount bricks-and-mortar store, and on 8% of their purchases from the Web site. We do not find significant differences in the extent of discount offered and the frequency of discounts offered across channels, because the variation in these factors is high within each channel.

Customers seem to shop more in the bricks-and-mortar stores (full-price and discount stores) than at the Web site. The gross profit per transaction is the highest for the full-price bricks-and-mortar stores ($260) and is significantly different ($p < .01$) from the gross profit per transaction for the Web site ($189) and the discount bricks-and-mortar stores ($122). The difference between the number of transactions per quarter a customer makes in two channels and the number of transactions per quarter a customer makes in a single channel is significant and positive (average difference = 3.2, $p < .01$). We observe a similar phenomenon when we compare transaction levels when a customer shops in three channels with transaction levels when a customer shops in two channels. This implies that there is little or no cannibalization in sales from the previous channels when a customer adopts a new channel.

From the population of customers, we randomly sampled 1165 and 379 customers to create the calibration and holdout samples, respectively. Among the 1165 customers in the calibration sample, 250 were three-channel customers (i.e., we observe the duration to adopt both the second and the third channel for these customers), 463 were two-channel customers (i.e., we observe the duration to adopt the second channel, but the duration to adopt the third channel is censored), and 452 were single-channel shoppers (i.e., the duration to adopt both the second and the third channels is censored). For both the two-channel and the three-channel customers, we have two observations per customer—one observation for the duration to adopt the second channel and one observation for the duration to adopt the third channel. For the single-channel customers, we have only one observation per customer—the censored duration to adopt the second channel. The distribution of single-, two-, and three-channel customers in the holdout sample is similar to that of the calibration sample. We use the holdout sample to evaluate the predictive accuracy of the proposed model. Table 2 provides the operationalization of the drivers on channel adoption duration.

Duration to Adopt the Second Channel

We measure basket size as the ratio of the sum of the number of items a customer bought in each transaction to the number of transactions the customer made when shopping in a single channel. Similarly, we measure cross-buying as the ratio of the sum of the number of different product categories a customer bought at each transaction to the total number of transactions the customer made when shopping in a single channel. We measure proportion of returns as the ratio of the number of return occasions to the number of transactions a customer made when shopping in a single channel. We measure frequency of marketing communications as the ratio of the sum of the number of marketing communications sent by the firm between two consecutive customer transactions to the total number of transactions the customer made.

We measured level of price discounts as the product of the probability that a discount would be available for a customer in a given shopping trip (Prob[dis]) and the average

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[8] Fewer than 1% of the transactions made by a customer are through the use of cash. Therefore, we have reliable information on when and through which channel the customer made his or her first transaction.

TABLE 2
Operationalization of Drivers

Variable	Operationalization
Drivers of Duration to Adopt Second Channel	
Basket size	Total number of items bought per transaction when shopping in a single channel
Cross-buying	Number of different products categories bought per transaction when shopping in a single channel
Level of price discounts	Product of Prob(dis) and APDS when shopping in a single channel, where Prob(dis) = the ratio of number of transactions when a discount was available to the number of transactions and APDS = average percentage difference between the regular and the purchase price for a product that was bought on discount
Proportion of returns	Ratio of number of returns to number of transactions when shopping in a single channel
Purchase frequency	Reciprocal of the average interpurchase time when shopping in a single channel
Frequency of marketing communications	Number of marketing communications (direct mail or e-mail) between two transactions when shopping in a single channel
Travel cost proportion	Ratio of the distance to the closet store in the current channel to the sum of the distances to the closet store in all available channels
IPA proportion	Ratio of the IPA in the current channel to the number of channels with IPA among all the available channels (equal to 1 if the transaction channel is either discount or full price and 0 if otherwise)
Drivers of Duration to Adopt Third Channel	
Basket size	Total number of items bought per transaction when shopping in two channels
Cross-buying	Number of different products categories bought per transaction when shopping in two channels
Level of price discounts	Product of Prob(dis) and APDS when shopping in two channels, where Prob(dis) = the ratio of number of transactions when a discount was available to the number of transactions and APDS = average percentage difference between the regular and the purchase price for a product that was bought on discount
Proportion of returns	Ratio of number of returns to number of transactions when shopping in two channels
Purchase frequency	Reciprocal of the average interpurchase time when shopping in two channels
Frequency of marketing communications	Number of marketing communications (direct mail or e-mail) between two transactions when shopping in two channels
Travel cost proportion	Ratio of the sum of the distances to the closet stores in each transaction channel (when shopping in two channels) to the sum of the distances to the closet store in all available channels
IPA proportion	Ratio of the IPA in the current channels to the number of channels with IPA among all the available channels (equal to 1 if the transaction channel is either discount or full price and 0 if otherwise)

percentage savings the customer obtains when the discount is available (APDS). We interpret the level of price discounts as the percentage savings a customer obtains in any shopping trip, allowing for the nonavailability of discounts on every customer transaction. We measure frequency of transactions as the reciprocal of the average interpurchase time for the customer when shopping in a single channel. In our data, the offline channels (full-price and discount bricks-and-mortar stores) have higher travel costs than the online channel. Conversely, the online channel has a higher cost related to the nonavailability of IPA, whereas the two offline channels have IPA and, thus, lower interaction costs. Therefore, there is no a priori reason to expect that the channels differ in interaction costs other than their travel costs and IPA. As we explained previously, measuring these variables on a per transaction basis controls for the possibility that customers who have a longer duration for channel adoption can also have higher levels for the cumulative values of basket size, cross-buying, the number of marketing communications, and returns.

Duration to Adopt the Third Channel

We measured the drivers of the third-channel adoption duration similar to the drivers of second-channel adoption duration, except that we used customer transactions when shopping in two channels instead of customer transactions when shopping in a single channel. In Table 3, we provide the descriptive statistics and the correlation matrix of the drivers of channel adoption used in our study. On average, the customers in the calibration sample take approximately 15 months to adopt a second channel. Among the customers who also adopted a third channel, the duration for adopting a third channel is approximately 10 months. The correlation matrix shows that multicollinearity is not a serious threat in our analyses.

Results and Discussion

We estimated four versions of the proportional hazard model (based on the likelihood function in Equation 8) using the customers selected in the calibration sample through MCMC methods (as we explain in the Appendix). Model 1 has no covariates and no frailty, Model 2 has frailty but no covariates, Model 3 has covariates but no frailty, and Model 4 has both covariates and frailty. We used 10,000 iterations for burn-in and 20,000 iterations to form the posterior sample. The line plots of the posterior sample revealed that the algorithm converged satisfactorily. We report the results of our analyses in Table 4.

Model Fit

We use the aggregate log conditional predictive ordinate (CPO) for evaluating the in-sample fit of the four competing models (Gelfand, Dey, and Chang 1992). Similar to the log-likelihood, a higher value of the aggregate log CPO is interpreted as a better model fit. Table 4 shows that Model 4 has the highest aggregate log CPO (–13,383) among the four models. Compared with Model 3, we calculate the psuedo-Bayes factor (PsBF) of Model 1 as the difference between the aggregate log CPO of Model 4 and that of Model 3 (equal to 39); the results indicate strong support for Model 4 over Model 3 and for including the frailty term in our model formulation.[9] The PsBF measures also provide strong support for Model 4 over Models 1 and 2 (see Table 4). Overall, the model comparisons suggest that a proportional hazard model with both the proposed covariates and the frailty term provides the best in-sample fit.

Predictive Accuracy

To evaluate the predictive accuracy of our model, we used the posterior distribution of the parameters obtained from the calibration sample to simulate the predictive distribution of hazard rates for the customers in the holdout sample. We then obtained the duration for channel adoption in the holdout sample from the inverse cumulative distribution function corresponding to the hazard function in Equation 4. For customers in the holdout sample, we obtained the frailty parameter (w_i) through a random draw from the frailty distribution (Equation 7), whose parameters (κ, $1/\kappa$) we estimated using the calibration sample. We then evaluated the mean absolute deviation (MAD) between the predicted duration to adopt a second channel and the predicted duration to adopt a third channel with the observed durations to adopt in the holdout sample. We note that the MAD comparisons could be performed only for the uncensored observations. Approximately 22% and 20% of the customers in the holdout sample had censored observations for the duration to adopt the third channel and the duration to adopt the second channel, respectively.

Similar to the in-sample fit comparisons, we find that Model 4 provides better predictions of the channel adoption duration in the holdout sample (MAD for Event 1 = 5.0 months, and MAD for Event 2 = 4.0 months) than does Model 3 (MAD for Event 1 = 8.1 months, and MAD for Event 2 = 6.0 months).[10] Model 4 also provides better predictions of channel adoption durations than do Models 1 and 2 (see Table 4). We also used the average duration to adopt the second and third channels from the calibration sample as a naive estimate of the duration for adopting the second and third channels, respectively. The MAD of the naive estimate in the holdout sample was 11 months for Event 1 and 10 months for Event 2. Finally, we calculated the hit ratio of the number of customers predicted to have channel adoption durations (second and third) outside the observation window and the number of customers observed to have censored durations in the holdout sample. We find that the predictions from Model 4 match the observations in the holdout sample for 80% of the customers, whereas the predictions from Model 4 match only 69% of the observations in the holdout sample. Thus, we use the results of Model 4 to discuss the parameter estimates.

Baseline Hazard

The shape of the baseline distribution ($\alpha = 1.65$) is significantly different from 1, implying that an exponential distribution would not be appropriate for modeling the baseline hazard in our context. The scale parameters ($\lambda_2 = 4.8e\text{-}05$, and $\lambda_3 = 1.8e\text{-}04$) imply that the customers' baseline hazards vary between the second- and the third-channel adoption (see Figure 2). Although the baseline hazard increases for both the second- and the third-channel adoption durations, it is flatter and has a lower risk (i.e., longer duration) for the second-channel adoption. This implies that similar to the descriptive statistics, the baseline hazards also indicate that, in general, customers take a longer time to adopt the second channel than to adopt the third channel.

Antecedents of Channel Adoption Duration

We discuss the risk ratio to understand the relative impact of a variable on the hazard of channel adoption (the parameter estimates themselves appear in Table 4). We can

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[9] When Model 1 is compared with Model 2, PsBF values greater than 20 can be considered a significant support for Model A over Model B (Raftery 1996).

[10] Event 1 is the adoption of the second channel, and Event 2 is the adoption of the third channel.

TABLE 3
Descriptive Statistics and Correlation Matrix

Variable	M	SD	Duration (Days)	Basket Size	Cross-Buying	Level of Price Discounts	Proportion of Returns	Purchase Frequency	Frequency of Marketing Communi-cations	Travel Cost Proportion	IPA Proportion
Duration to Adopt Second Channel											
Duration (days)	489	436	1								
Basket size	48.6	88.3	.06	1							
Cross-buying	1.8	1.5	–.45	–.17	1						
Level of price discounts	.005	.08	–.08	–.001	.07	1					
Proportion of returns	.01	.06	.15	.06	–.15	.02	1				
Purchase frequency	.02	.02	–.31	.13	.008	.12	.08	1			
Frequency of marketing communications	5.5	10.9	–.1	–.14	.16	.02	–.06	–.13	1		
Travel cost proportion	.41	.29	.25	.03	–.03	–.02	.07	–.08	–.37	1	
IPA proportion	.23	.42	–.25	–.15	.05	–.04	–.11	.03	.47	–.67	1
Duration to Adopt Third Channel											
Duration (days)	338	330	1								
Basket size	52.1	78.2	.16	1							
Cross-buying	1.8	.7	–.28	–.1	1						
Level of price discounts	.009	.08	–.12	–.03	.08	1					
Proportion of returns	.02	.08	.16	.09	–.17	.03	1				
Purchase frequency	.02	.04	–.31	.12	–.01	–.02	.03	1			
Frequency of marketing communications	9.2	14.6	.21	–.1	.18	.05	.04	.07	1		
Travel cost proportion	.72	.26	.36	.06	–.005	.07	.04	–.02	–.07	1	
IPA proportion	.43	.49	–.37	–.09	–.1	.06	.09	–.06	–.19	–.6	1

TABLE 4
Results from Model Estimation

	Model 1: Proportional Hazard with No Covariates and No Frailty	Model 2: Proportional Hazard with Frailty and No Covariates	Model 3: Proportional Hazard with Covariates and No Frailty	Model 4: Proportional Hazard with Covariates and Frailty
Baseline Distribution				
λ_1 (second-channel adoption)	1.3E-3***	9.2E-4***	1.8e-4***	4.8e-5***
	(9.2E-4)	(1.8E-4)	(2.9e-05)	(1.2e-05)
λ_2 (third-channel adoption)			5.7e-4***	1.8e-04***
			(8.3e-5)	(5.86e-05)
α	1.5***	1.1***	1.4***	1.6***
	(.06)	(.04)	(.02)	(.06)
κ		4.97***		4.9***
		(2.7)		(2.6)
Customer Heterogeneity				
Income			.04**	.02
			(.02)	(.03)
Gender (female = 1)			.13***	.15***
			(.04)	(.07)
Adoption of Second-Channel Interaction Characteristics				
Purchase-Related Attributes				
Basket size			.33***	.45***
			(.07)	(.09)
Square of basket size			–.13***	–.19***
			(.07)	(.09)
Cross-buying			–.55***	–.72***
			(.03)	(.05)
Level of price discounts			–.04***	–.07***
			(.03)	(.04)
Proportion of returns			–.39***	–.49***
			(.10)	(.13)
Square of proportion of returns			.42***	.51***
			(.09)	(.11)
Frequency-Related Attributes				
Purchase frequency			–.81***	–1.1***
			(.02)	(.09)
Frequency of marketing communications			–.37***	–.62***
			(.09)	(.14)
Square of frequency of marketing communications			.15***	.29***
			(.08)	(.11)
Channel-Related Attributes				
Travel cost proportion			–.19***	–.25***
			(.05)	(.07)
IPA proportion			.17***	.18***
			(.11)	(.10)
Adoption of Third-Channel Interaction Characteristics				
Purchase-Related Attributes				
Basket size			.18***	.26***
			(.07)	(.10)
Square of basket size			–.08*	–.11***
			(.06)	(.07)
Cross-buying			–.35***	–.56***
			(.02)	(.06)
Level of price discounts			–.06*	–.05*
			(.05)	(.04)
Proportion of returns			.48***	.52***
			(.10)	(.15)

TABLE 4
Continued

	Model 1: Proportional Hazard with No Covariates and No Frailty	Model 2: Proportional Hazard with Frailty and No Covariates	Model 3: Proportional Hazard with Covariates and No Frailty	Model 4: Proportional Hazard with Covariates and Frailty
Frequency-Related Attributes				
Purchase frequency			–.68***	–1.13***
			(.02)	(.15)
Frequency of marketing communications			–.85***	–.98***
			(.07)	(.10)
Square of frequency of marketing communications			–.40***	.40***
			(.06)	(.09)
Channel-Related Attributes				
Travel cost proportion			–.60***	–.70***
			(.06)	(.08)
IPA proportion			.20***	.26***
			(.12)	(.17)
Frailty (w)		1.0		1.04
		(.33)		(.22)
Aggregate log CPO[a]	–16,214	–14,278	–13,306	–13,283
Psuedo-Bayes factor (PsBF)[b]	2931	995	39	
MAD for adopting second channel (months)	15.5	14.0	8.1	5.0
MAD for adopting third channel (months)	15.1	12.1	6.0	4.0

*More than 90% of the posterior distribution does not contain zero.

**More than 95% of the posterior distribution does not contain zero.

***More than 99% of the posterior distribution does not contain zero

[a] The aggregate of the log of the CPO is computed similarly to Gelfand, Dey, and Chang (1992).

[b] Calculated with Model 4 as the base model. The PsBF for Model 1 is equal to the difference between the aggregate log CPO values for Model 4 and Model 1. The PsBF for Models 2 and 3 is calculated similarly.

Notes: The coefficients measure the influence of the covariates on channel adoption duration.

interpret the risk ratio as the percentage change in the hazard for a one-unit increase in the independent variable, after we control for all other independent variables. We calculated the risk ratio as ([exp{β} – 1]100). The risk ratios appear in Table 5.

Interaction Characteristics: Purchase-Related Attributes

Basket size. As hypothesized (H_1), we find that basket size has a nonlinear relationship with both the second- and the third-channel adoption durations. The inverted U-shaped influence of basket size implies that customers who purchase an intermediate number of items on each shopping trip would take longer to adopt an additional channel than customers who purchase either a very small number of items or a very large number of items. The risk ratio for basket size indicates that up to a certain threshold, the second-channel adoption duration is longer by 40%, and beyond the threshold, the second-channel adoption is shorter by 40% for a unit increase in basket size (i.e., purchasing one additional item at each transaction) across single-channel customers. Similarly, up to a certain threshold, the third-channel adoption duration is longer by 19%, and beyond the threshold, the third-channel adoption duration is shorter by 19% for a unit increase in basket size across two-channel customers.

Cross-buying. The results provide support for our hypothesis (H_2) that customers who purchase across product categories (i.e., exhibit a higher level of cross-buying) have shorter channel adoption durations. The risk ratio indicates that the duration for adopting a second channel is shorter by 51% for a unit increase in cross-buying (i.e., purchasing from one additional product category at each transaction) across single-channel customers. Across two-channel customers, the third-channel adoption duration decreases by 51% for a unit increase in cross-buying.

Level of price discounts. As hypothesized (H_3), we find evidence for a negative relationship between an increase in the level of price discounts and channel adoption duration. The risk ratio indicates that the duration to adopt the second channel is shorter by 7% for a unit increase in the level of price discounts (i.e., one additional dollar in the discounts expected during any transaction) across single-channel customers, and the duration to adopt the third channel is shorter by 5% for a unit increase in the level of discounts across two-channel customers. Our results imply that though discounts may be primarily considered a tool for acquiring new customers (Gupta 1988), they can also be effective in growing the relationship with current customers.

Proportion of returns. Our results support the hypothesis that there is a U-shaped relationship between the propor-

FIGURE 2
Baseline Hazard for Second- and Third-Channel Adoption Duration

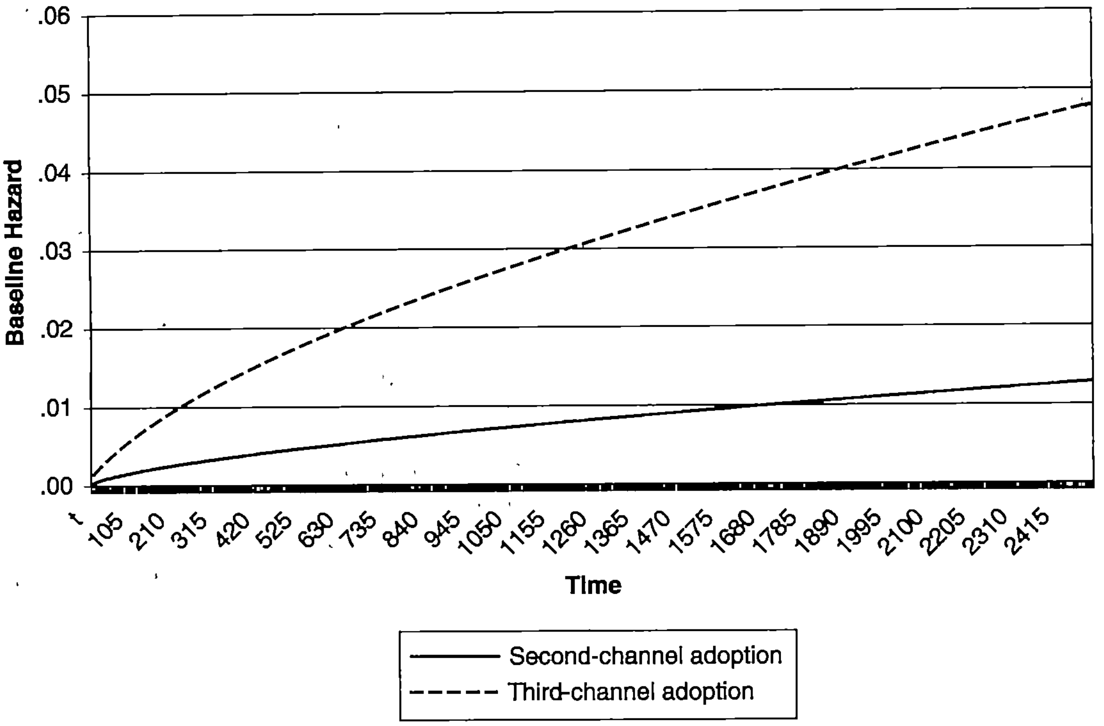

TABLE 5
Risk Ratios for Drivers of Channel Adoption Duration

Driver	Second-Channel Adoption Duration: Risk Ratio (%)	Second-Channel Adoption Duration: Effect on Adoption Duration	Third-Channel Adoption Duration: Risk Ratio (%)	Third-Channel Adoption Duration: Effect on Adoption Duration
Interaction Characteristics: Purchase-Related Attributes				
Basket size	40	∩	19	∩
(Basket size)^2				
Cross-buying	–51	–	–42	–
Level of price discounts	–7	–	–5	–
Proportion of returns	4	∪	68	+
(Proportion of returns)^2			N.A.	N.A.
Interaction Characteristics: Frequency-Related Attributes				
Purchase frequency	–67	–	–68	–
Frequency of marketing communications	12	∪	3	∪
(Frequency of marketing communications)^2				
Interaction Characteristics: Channel-Related Attributes				
Travel cost proportion	–22	–	–50	–
IPA proportion	20	+	30	+

Customer Heterogeneity

	Risk Ratio (%)	Expected Effect
Income	N.A.	N.A.
Gender (female = 1)	17	N.A.

Notes: N.A. = not applicable

tion of returns and a customer's duration for adopting a second channel (H_{4a}). Regarding two-channel customers, we find that customers with a higher proportion of returns have a longer third-channel adoption duration, in support of H_{4b}. The risk ratio indicates that up to a certain threshold, the second-channel adoption duration is shorter by 4%, and beyond the threshold, the second-channel adoption is longer by 4% for a unit increase in the proportion of returns across single-channel customers. Across two-channel customers, the duration to adopt a third channel is longer by 68% for a unit increase in the proportion of returns.

Customer returns provide firms with an opportunity to address concerns about the customer–firm relationship. The U-shaped relationship for single-channel customers indicates that customers who make intermediate levels of returns adopt a second channel faster than customers who make very few or too many returns. However, the higher the number of returns a two-channel customer makes, the longer is the customer's third-channel adoption duration. We infer that allowing a smooth and costless product return process is essential for encouraging customers to shop across multiple channels. Overall, we find that with the exception of the proportion of returns, the product-related interaction attributes (basket size, cross-buying, and level of price discounts) have greater impacts on single-channel customers than on two-channel customers.

Interaction Characteristics: Frequency-Related Attributes

Purchase frequency. As hypothesized (H_5), we find that customers with a higher purchase frequency have shorter channel adoption duration. The risk ratio indicates that across single-channel customers, the duration to adopt a second channel decreases by 67% for a unit increase in purchase frequency. Similarly, across the two-channel customers, the duration to adopt a third channel decreases by 68% for a unit increase in purchase frequency.

Frequency of marketing communication. We find strong support for our hypothesis that there is a U-shaped relationship between the frequency of marketing communication and channel adoption duration (H_6). Up to a certain threshold, the second-channel adoption duration is shorter by 12%, and beyond the threshold, the second-channel adoption is longer by 12% for a unit increase in the frequency of marketing communications (i.e., an additional marketing communication between two transactions) across single-channel customers. Similarly, across two-channel customers, the third-channel adoption duration is shorter by 13% up to a certain threshold and is longer by 13% beyond the threshold for a unit increase in the frequency of marketing communications.

Overall, our results support the notion that higher interaction frequency leads to relationship development and shorter channel adoption duration. We also find that the reciprocal communications from the firm are important in influencing customer channel adoption duration. Although the influence of purchase frequency on channel adoption duration is similar for both single- and two-channel customers, the difference in channel adoption duration for a unit difference in the frequency of marketing communications is higher for two-channel customers than for single-channel customers. This implies that managers should be more cautious about not exceeding the optimal level of marketing communications for two-channel customers and single-channel customers.

Interaction Characteristics: Channel-Related Attributes

Travel cost proportion. As hypothesized (H_7), we find that the proportion of the travel cost in the current channels is negatively related to the duration to adopt for both single-channel and two-channel customers. The risk ratio indicates that the second- (third-) channel adoption duration decreases by 22% (50%) for a unit increase in the travel cost proportion. We find support for the conventional wisdom that travel costs, which increase with distance, influence customers' store choices (Bell, Ho, and Tang 1998). This result has important implications for the location of a new store and for the store format in the new location.

IPA proportion. We find strong support for the notion that (at least for apparel manufacturers) the time lag between when the product is ordered and when the product is available is an important determinant of channel adoption duration. Our results indicate that across single- (two-) channel shoppers, the second- (third-) channel adoption duration is longer by 20% (30%) for a unit increase in IPA proportion. These results imply that managers should try to find alternative ways (e.g., free shipping and handling) to reduce customer costs of shopping in channels without IPA. Our results indicate that the influence of channel-related interaction attributes is greater for two-channel customers than for single-channel customers.

Observed Customer Heterogeneity (Income and Gender)

We find that male customers have shorter channel adoption duration and that income is not related to channel adoption behavior. The adoption duration for female customers is 17% longer than the adoption duration for male customers. The information in customer heterogeneity variables adds explanatory power in the channel adoption duration model beyond the interaction characteristics.

Managerial Implications

Do Customers Provide Higher Profits When They Shop in Multiple Channels?

Our longitudinal analysis implies that managers have the opportunity to grow customer profits by encouraging customers to shop in multiple channels. Overall, providing a multichannel experience to customers has the potential to improve two critical aspects of CRM: customer retention and customer growth. There could be several reasons that customers provide more profits when they shop in multiple channels. One rationale is that firms can provide several add-on services to customers through their multiple channels (e.g., order online, pickup offline). Customers who shop in multiple channels (regardless of their purchase activity) are exposed to the services the firm provides and therefore are expected to be more satisfied with the firm and develop a deeper relationship with the firm. These factors translate into multichannel customers potentially allocating a higher share of wallet to the firm and therefore providing higher profits.

How Do Customer–Firm Interaction Characteristics Affect Channel Adoption Duration?

We find strong support for using the social exchange theory to understand customer channel adoption duration. The importance of the interaction characteristics varies between single- and two-channel customers. Frequency-related interaction characteristics (purchase frequency and frequency of marketing communication) have the greatest influence on second-channel adoption duration. This result adds to recent findings that heavy users (i.e., those with higher purchase frequency and spending levels) have a greater preference for shopping in multiple channels (Gensler, Dekimpe, and Skiera 2007). In contrast, proportion of returns has the highest influence on third-channel adoption duration, followed by the frequency-related attributes. This implies that managers need to take every effort to address product returns from single-channel customers because addressing initial product returns is necessary for relationship development and faster channel adoption. The results also add to the growing belief in the literature that marketing communications are critical in influencing customer channel choices (Neslin et al. 2006). However, our results also urge managers to be aware that there is an optimal frequency of communications for each customer, and overcommunicating to customers can have dysfunctional consequences, such as longer channel adoption durations.

Variation across customers in purchase-related attributes (except proportion of returns) has a greater impact on the duration to adopt the second channel than on the duration to adopt the third channel. In contrast, variation across customers in the channel-related attributes has a greater influence on the third-channel adoption duration than on the second-channel adoption duration. This implies that managers can expect better responses by directing a higher level of discounts to single-channel customers than to two-channel customers. In addition to targeting customers who purchase frequently, the channel adoption campaigns to single-channel customers should also target customers who have either very small or very large basket sizes and who purchase across different categories. Although the influence of customer heterogeneity factors may not be generalizable, our results imply that male customers are more likely to adopt an additional channel faster.

Does Channel Adoption Duration Change on the Basis of a Customer's Current and Future Transaction Channels?

Information about how channel adoption durations vary depending on a customer's current transaction channels would enable managers to target certain channels for multichannel marketing. On the basis of the risk ratios in Table 5, we find that the second-channel adoption duration for customers who first adopt the full-price store is longer than the second-channel adoption duration for customers who first adopt the discount store by 27% and is longer than the second-channel adoption duration for customers who first adopt the Web site by 6%. Customers who adopt the discount store first have shorter second-channel adoption duration than customers who first adopt the Web site by 21%. The third-channel adoption duration for customers who shop either in the discount store or at the Web site is shorter than the third-channel adoption duration of customers who shop in either the full-price store or the discount store by .8% and is shorter than the third-channel adoption duration for customers who shop either in the full-price store or at the Web site by 36%. The third-channel adoption duration for customers who shop in either the full-price store or the discount store is shorter than the third-channel adoption duration of customers who shop either in the full-price store or at the Web site by 35%.[11]

In addition to current transaction channels, channel adoption duration could vary systematically on the basis of the future transaction channels. We assessed the MAD of the model predictions in the holdout sample for each current and future channel combination. Specifically, we split the holdout sample into six subsamples based on the second- and third-channel adoption durations. We found that the MAD of model predictions ranged from 4.2 (3.7) to 5.5 (4.1) months among the six subsamples for the second- (third-) channel adoption durations. This is in line with the MADs of 5 and 4 months for the second- and third-channel adoption durations, respectively, when all the subsamples are pooled. Therefore, there is no reason to believe that the channel-related attributes we included in the conceptual framework fail to capture any systematic variation in channel adoption durations related to a customer's current and future transaction channels.

Managing Multichannel Marketing Resources

In our context, we do not expect that the parameter estimates are biased because we did not model (1) the firm actions related to targeting customers for multichannel shopping (i.e., the supply side) and (2) the customer expectations of incentives that can be obtained from multichannel shopping (Frances 2005). However, managers need to be cautious when adopting our modeling framework for managing multichannel marketing resources. The customer–firm interaction characteristics and their corresponding impact on channel adoption duration are based on a retrospective analysis of customer transactions with a firm, and our modeling framework assumes a constant managerial strategy during the analyses time frame. Prospective actions that are based on the retrospective analyses we presented in this study, such as targeting customers for multichannel shopping when they are ready to adopt another channel, imply changing the managerial strategy, and the impact of customer–firm interaction characteristics on channel adoption duration could potentially change after a new strategy is implemented.[12] Thus, we recommend that managers adopt a phased approach for managing multichannel marketing resources.

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[11] We find similar results when we replace travel cost proportion and IPA proportion with channel-related dummies. The results are available on request.

For illustration, consider a firm that wants to adopt a strategy in which it sends direct mail to single-channel customers to inform them about the multiple channels available for transaction, but only when the single-channel customers are expected to adopt a second channel. Before implementing the new strategy for the entire customer base, we recommend that the firm conduct a field experiment for a sample of the customers. Customers who participate in the field experiment would be selected for the mailing effort through a stratified random sampling process. The weights for the stratified sampling process are proportional to the customer's propensity to adopt a new channel during the experiment time frame. The model we present and the customer–firm interaction characteristics we identify would enable managers to predict a customer's hazard for channel adoption at each period. Customer responses during the experiment could then be used to assess (1) the return on investment of the new strategy and (2) whether the impact of customer–firm interaction characteristics changed after adopting the new strategy. If the firm realized return-on-investment improvements from the new strategy, our model would need to be updated to incorporate explicitly the firm's strategy during the experiment to develop optimal resource allocation guidelines for multichannel marketing. The field experiment would also enable managers to assess the true effectiveness of the model recommendations.

Limitations and Further Research

Our results are based on customer behavior in the apparel product category. We expect that the influence of the drivers at the construct level (i.e., purchase-related, channel-related, and frequency-related attributes of customer–firm interactions) and the shared-frailty model framework for predicting channel adoption duration are generalizable to other product categories. However, further replications in other industries would be required to obtain empirical regularities on the relative influence of the variables, such as basket size on single- and two-channel customers. Such replications would be beneficial for developing theories that can improve the effectiveness of multichannel marketing. Another limitation of our study is that we do not allow for the possibility that a single purchase can be related to two channels. For example, many mail-order-catalog firms also have online channels. This leads to a significant "flowback" issue in which customers receive the catalog in the mail and then go online to place the order. This is not a major restriction in our context, because the retailer we study does not offer a direct mail catalog. The model framework we propose here would need to be suitably modified in instances in which a "dual-channel" purchase process is likely. Further research that explores customer attitudes (motivations and apprehensions) toward shopping in multiple channels would help managers design effective channel migration campaigns.

In the customer database we used, the primary mode of communication with the customers was through direct mail. Thus, we were not able to investigate whether a customer's preferences for modes of communication vary with the transaction channels he or she uses. Given that the cost of communication varies across the different modes (e.g., salespeople, direct mail, telephone sales, e-mail), further research that explores the link between modes of communication and channel adoption rate would be valuable for profitable multichannel customer management.

Appendix
Conditional Distributions and MCMC Estimation Algorithm

Likelihood Function

Let δ_{ij} denote the indicator variable, which is 1 if t_{ij} is an actual observed time to adoption and is 0 if it is a censored observation. Let g_{12} equal 1 and g_{i3} equal 0 for single-channel customers (i.e., $\delta_{i2} = 0$, and $\delta_{i3} = 0$). For multichannel customers—both two-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 0$) and three-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 1$) customers—let g_{i2} and g_{i3} equal 1. The variables (t_{ij}, δ_{ij}, g_{ij}, X^*_{ij}) are observed for channel adoption events j = 2, 3 and customers i = 1, ..., n, where X^*_{ij} includes event-specific and common covariates. Let all such factors be denoted as $\tilde{D}$. Let $\tilde{W}$ = (w_1, ..., w_n) denote the vector of unobserved frailties. We refer to ($\tilde{D}$, $\tilde{W}$) as the complete data. The likelihood has the following form:

$$L = \prod_{i=1}^{n}\prod_{j=2}^{3}\left[(\lambda_j \gamma t_{ij}^{\gamma-1} w_i \vartheta_{ij})^{\delta_{ij}} \times \exp(-\lambda_j t_{ij}^{\gamma} w_i \vartheta_{ij})\right]^{g_{ij}},$$

where $\vartheta_{ij} = e^{\beta_0' X_{i0}} \times e^{\beta_2' X_{i2} \varphi_2} \times e^{\beta_3' X_{i3} \varphi_3}$ and $\varphi_j = 1$ if the observation represents the jth channel adoption and 0 if otherwise.

Prior Specifications

The product prior specifications for the model parameters (assuming independence) are as follows: For the common covariates, we assume that the prior distribution $\pi(\beta_{0s})$ is normal (c_{0s}, d_{0s}) for s = 1, ..., p_0; the prior distribution for covariates of second-channel adoption duration (Event 1) $\pi(\beta_{2s})$ is normal (c_{2s}, d_{2s}) for s = 1, ..., p_2; and the prior distribution for covariates of third-channel adoption duration (Event 2) $\pi(\beta_{3s})$ is normal (c_{3s}, d_{3s}) for s = 1, ..., p_3. The prior distribution for κ is $\pi(\kappa)$ = Gamma (c_k, c_k), for $\pi(\lambda_j)$ is Gamma ($c_{\lambda j}$, $c_{\lambda j}$), and for $\pi(\gamma)$ is Gamma (1, c_γ). The values of the hyperparameters are chosen to correspond to noninformative prior assumptions.

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[12] A reasonable estimate of how the parameter estimates might change can be obtained by comparing the parameter estimates for customers who were (1) touched heavily and (2) touched less in the past. We find that the substantive conclusions of our study are the same for both groups, leading us to believe that the influence of customer–firm interaction characteristics would not change dramatically if a firm adopts our model framework.

MCMC Algorithm

The MCMC algorithm proceeds by sampling sequentially from the following conditional distributions. Given all other parameters and the data, the complete conditional distribution of λ_j is proportional to a gamma distribution as follows:

$$p(\lambda_j|\gamma, t_{ij}, w_i, \vartheta_{ij})$$

$$\sim \text{gamma}\left(\sum_i \delta_{ij}g_{ij} + c_{\lambda_j} - 1,\ \sum_i v t_{ij}^{\gamma} w_i \vartheta_{ij} g_{ij} + c_{\lambda j}\right).$$

The complete conditional distribution of γ, given all other parameters, is proportional to

$$p(\gamma|\lambda, t_{ij}, w_i, \vartheta_{ij}) \propto \gamma^{\sum_i \sum_j \delta_{ij} * g_{ij}} \left(\prod_{i=1}^{n}\prod_{j=2}^{3} t_{ij}^{\delta_{ij}g_{ij}}\right)^{\gamma}$$

$$\times \exp\left(-\sum_i \sum_j \lambda_j t_{ij}^{\gamma} w_i \vartheta_{ij} g_{ij} - \gamma c_{\gamma}\right).$$

We used the ratio of uniforms method to generate samples. The complete conditional distribution of κ, given all other parameters, is proportional to

$$p(\kappa|w_i) \propto \left(\prod_{i=1}^{n} w_i\right)^{\kappa} \frac{\kappa^{n\kappa + c_{\kappa} - 1}}{\Gamma(\kappa)^n} \exp\left[-\kappa\left(\sum_{i=1}^{n} w_i + c_{\kappa}\right)\right].$$

We use the Metropolis–Hastings algorithm to generate samples. For i = 1, …, n, the complete conditional distribution of w_i, given all other parameters and the data, is proportional to a gamma distribution as follows:

$$p(w_i|\delta_{ij}, \lambda, \gamma, t_{ij}, \vartheta_{ij}, \kappa)$$

$$\sim \text{gamma}\left(\sum_{j=2}^{3} \delta_{ij} g_{ij} + \kappa,\ \sum_{j=2}^{3} \lambda_j t_{ij}^{\lambda} \vartheta_{ij} g_{ij} + \kappa\right).$$

The complete conditional distributions of β_0 (the common regression parameters) is

$$p(\beta_{0s}|t_{ij}, w_i, \lambda, \gamma) \propto \prod_{i=1}^{n}\prod_{j=2}^{3}\Big[(e^{-\beta_0' X_{i0}})^{\delta_{ij}g_{ij}}$$

$$\times \exp(-\lambda_j t_{ij}^{\gamma} w_i \vartheta_{ij} g_{ij})\Big] \times \prod_{s=1}^{p\_0} \exp\left[\frac{-1}{2d_{0s}}(\beta_{0s} - c_{0s})^2\right].$$

The complete conditional distributions of β_2 (the regression parameters specific to Event 1) and β_3 (the regression parameters specific to Event 2) have the forms

$$p(\beta_{js}|t_{ij}, w_i, \lambda, \gamma) \propto \prod_{i=1}^{n}\prod_{j=2}^{3}\Big[(e^{-\beta_j' X_{ij} \vartheta_{ij}})^{\delta_{ij}g_{ij}}$$

$$\times \exp(-\lambda_j t_{ij}^{\gamma} w_i \vartheta_{ij} g_{ij})\Big] \times \prod_{s=1}^{p\_j} \exp\left[\frac{-1}{2d_{js}}(\beta_{js} - c_{js})^2\right].$$

We use the ratio of uniforms method to generate samples in each case.

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Neglected Outcomes of Customer Satisfaction

Although there is significant evidence that customer satisfaction is an important driver of firm profitability, extant literature has largely neglected two intermediate outcomes of customer satisfaction, namely, a firm's advertising and promotion efficiency and its human capital performance. On the basis of longitudinal analyses of large-scale secondary data from multiple sources, the authors find that customer satisfaction boosts the efficiency of future advertising and promotion investments. This finding can be explained by the possibility that customer satisfaction generates free word-of-mouth advertising and saves subsequent marketing costs. In addition, customer satisfaction has a positive influence on a company's excellence in human capital (employee talent and manager superiority). This finding is highly novel, indicating that human resources managers should have a strong interest in customer satisfaction as well. Finally, the authors investigate the moderating influence of market concentration on both relationships. The uncovered results have important implications for marketers in their dialogue with financial executives and human resources managers.

Many academics would certainly agree that customer satisfaction is a central construct in marketing research. According to Keiningham, Munn, and Evans (2003, p. 37), "both practitioners and academics have accepted the premise that customer satisfaction results in customer behavior patterns that positively affect business results." In this context, Seiders and colleagues (2005, p. 26) state that "marketing literature consistently identifies customer satisfaction as a key antecedent to loyalty and repurchase." Furthermore, Szymanski and Henard (2001, p. 16) argue that "customer satisfaction has come to represent an important cornerstone for customer-oriented business practices across a multitude of companies operating in diverse industries." Finally, Mittal and Kamakura (2001, p. 131) add that "customer satisfaction management has emerged as a strategic imperative for most firms."

Indeed, customer satisfaction has attracted significant research interest for more than two decades. In particular, researchers have examined theoretical and conceptual underpinnings of customer satisfaction (e.g., Fornell et al. 1996; Luo and Bhattacharya 2006; Oliver 1997; Rust et al. 2004). There is a multitude of scientific articles that address potential antecedents of customer satisfaction (e.g., Anderson and Sullivan 1993; Bolton and Lemon 1999; Oliver 1980; Szymanski and Henard 2001). In addition, many studies have investigated various outcomes of customer satisfaction. This is also the focus of our research.

Figure 1 provides an overview of previous empirical work on the outcomes of customer satisfaction. We distinguish four categories: customer-related, employee-related, efficiency-related, and overall performance-related outcomes. The last category is related to general performance outcomes, which are bottom line in nature. Most of the studies that fall into this category investigate financial performance outcomes of customer satisfaction. Overall, there is significant evidence in the marketing literature that customer satisfaction is an important driver of a firm's profitability. For example, Anderson, Fornell, and Lehmann (1994) and Rust, Moorman, and Dickson (2002) report a positive impact of customer satisfaction on financial performance measures, such as return on investment and return on assets. More recently, scholars have found that satisfaction boosts shareholder value by increasing cash flow growth and reducing its volatility (Fornell et al. 2006; Gruca and Rego 2005).

The other three categories of satisfaction outcomes are more specific and provide explanations for the positive impact of customer satisfaction on firm profitability. As Figure 1 shows, the majority of studies investigate customer-related outcomes (including customers' behavioral intentions and behaviors). The most central finding in this context is that satisfaction increases customer loyalty and influences future repurchase intentions and behavior (Fornell et al. 1996; Mittal and Kamakura 2001; Mittal, Ross, and Baldasare 1994; Olsen 2002). Another mechanism through which satisfaction can enhance profitability is related to pricing. Research shows that highly satisfied customers are willing to pay premium prices (Homburg, Koschate, and Hoyer 2005) and are less price sensitive (Stock 2005). Although Figure 1 reveals a large number of studies that examine outcomes of customer satisfaction, it also shows that two categories of outcomes have been neglected (and thus require further research): efficiency-related and employee-related outcomes.

In general, efficiency refers to the conversion ratio of organizational resource inputs to desirable goal outcomes (Bucklin 1978; Luo and Donthu 2006). To the best of our

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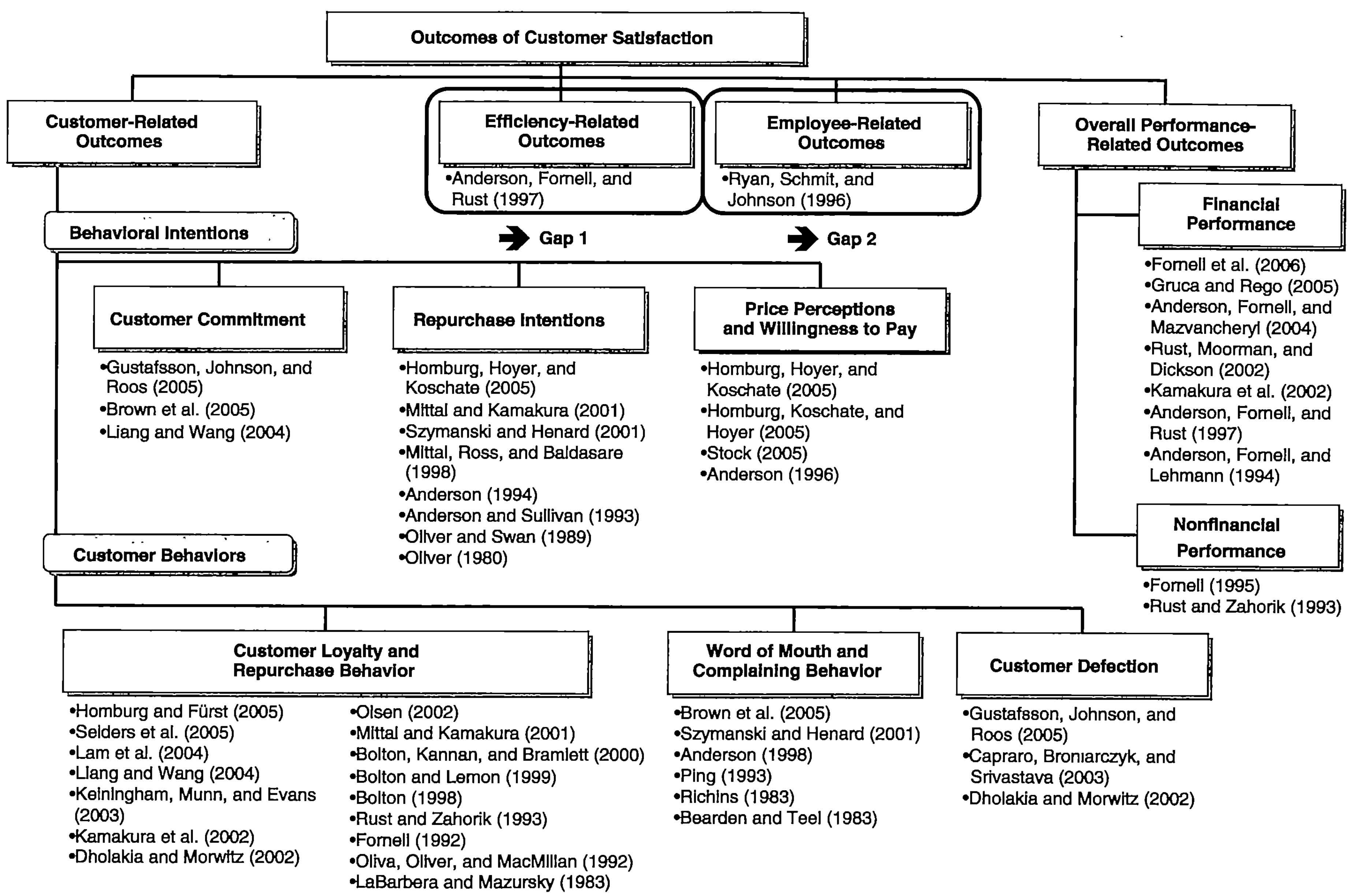
FIGURE 1
Outcomes of Customer Satisfaction: Framework and Empirical Studies


Outcomes of Customer Satisfaction
Customer-Related Outcomes
Efficiency-Related Outcomes
•Anderson, Fornell, and Rust (1997)
Employee-Related Outcomes
•Ryan, Schmit, and Johnson (1996)
Overall Performance-Related Outcomes
Gap 1
Gap 2
Behavioral Intentions
Customer Commitment
•Gustafsson, Johnson, and Roos (2005)
•Brown et al. (2005)
•Liang and Wang (2004)
Repurchase Intentions
•Homburg, Hoyer, and Koschate (2005)
•Mittal and Kamakura (2001)
•Szymanski and Henard (2001)
•Mittal, Ross, and Baldasare (1998)
•Anderson (1994)
•Anderson and Sullivan (1993)
•Oliver and Swan (1989)
•Oliver (1980)
Price Perceptions and Willingness to Pay
•Homburg, Hoyer, and Koschate (2005)
•Homburg, Koschate, and Hoyer (2005)
•Stock (2005)
•Anderson (1996)
Financial Performance
•Fornell et al. (2006)
•Gruca and Rego (2005)
•Anderson, Fornell, and Mazvancheryl (2004)
•Rust, Moorman, and Dickson (2002)
•Kamakura et al. (2002)
•Anderson, Fornell, and Rust (1997)
•Anderson, Fornell, and Lehmann (1994)
Nonfinancial Performance
•Fornell (1995)
•Rust and Zahorik (1993)
Customer Behaviors
Customer Loyalty and Repurchase Behavior
•Homburg and Fürst (2005)
•Seiders et al. (2005)
•Lam et al. (2004)
•Liang and Wang (2004)
•Keiningham, Munn, and Evans (2003)
•Kamakura et al. (2002)
•Dholakia and Morwitz (2002)
•Olsen (2002)
•Mittal and Kamakura (2001)
•Bolton, Kannan, and Bramlett (2000)
•Bolton and Lemon (1999)
•Bolton (1998)
•Rust and Zahorik (1993)
•Fornell (1992)
•Oliva, Oliver, and MacMillan (1992)
•LaBarbera and Mazursky (1983)
Word of Mouth and Complaining Behavior
•Brown et al. (2005)
•Szymanski and Henard (2001)
•Anderson (1998)
•Ping (1993)
•Richins (1983)
•Bearden and Teel (1983)
Customer Defection
•Gustafsson, Johnson, and Roos (2005)
•Capraro, Broniarczyk, and Srivastava (2003)
•Dholakia and Morwitz (2002)

knowledge, only one academic study has examined an efficiency-related outcome of customer satisfaction: Anderson, Fornell, and Rust (1997) show that customer satisfaction positively affects the ratio of sales to employee. Moreover, Mittal and colleagues (2005) and Rust, Moorman, and Dickson (2002) at least consider efficiency issues in their dual-emphasis approach, but they do not explicitly investigate the impact of customer satisfaction on efficiency-related outcomes. Notably, it is plausible that customer-related outcomes of customer satisfaction affect specific facets of productivity in the marketing domain. For example, because customer satisfaction induces customer behaviors such as free word-of-mouth advertising, firms with higher customer satisfaction may be more efficient in future marketing communications investments. Existing studies have not investigated this impact. Because research evolves as a progression, we need to evaluate the influence of customer satisfaction on the performance metric of advertising and promotion efficiency (i.e., the conversion ratio of sales to required advertising and promotion costs).

An approval or rejection of this influence is important to quantify the theory of the marketing productivity chain (Rust, Lemon, and Zeithaml 2004). According to Rust, Lemon, and Zeithaml (2004), marketing variables such as customer satisfaction should first influence some intermediate productivity metrics (i.e., marketing efficiency) before it has a financial impact. Managerially speaking, in their dialogue with chief financial officers (CFOs), marketing managers must show numbers to justify investments to increase customer satisfaction (*BusinessWeek* 2004; Gupta and Lehmann 2005; Rust et al. 2004). The CFO perspective on this issue often is that customer satisfaction costs money. Revealing a positive impact of customer satisfaction on future advertising and promotion efficiency would prove that customer satisfaction also saves subsequent marketing communications spending.

Previous research has also largely neglected employee-related performance outcomes of customer satisfaction. The only exception we are aware of is the work of Ryan, Schmit, and Johnson (1996), which reveals a positive impact of customer satisfaction on employee satisfaction. We argue that in times when customer satisfaction and corresponding surveys are publicly circulated (e.g., Spencer and Albergott 2004; Young 2006), superior levels of customer satisfaction may also have beneficial effects that are not driven by customer behaviors. For example, firms with higher customer satisfaction are more attractive employers and thus can often hire better people (because they signal financial success); as a result, such firms are able to enjoy superior human capital performance (e.g., Dess and Shaw 2001). Another possible explanation for an increase in firm human capital performance is that there is a more positive atmosphere in companies with satisfied and loyal customers because employees enjoy their jobs more (as a result of emotional contagion) and voluntarily work harder (Reichheld and Sasser 1990).

This underresearched issue (whether customer satisfaction enables the firm to increase its human capital performance) is highly relevant for managers. Indeed, human resources theory suggests that being an attractive employer with better human capital is a key success factor for firms (Becker 1964; Hatch and Dyer 2004; Hitt et al. 2001; Huselid 1995). Many organizations strive to become first-choice employers in their industries to acquire and retain "star" employees (e.g., *Fortune* 2006). Notably, if customer satisfaction helps the firm promote human capital excellence, human resources managers should have a strong interest in customer satisfaction as well.

The purpose of our study is to address the two neglected categories of customer satisfaction outcomes identified in Figure 1, namely, efficiency-related outcomes and employee-related outcomes. More specifically, we explore whether customer satisfaction affects a firm's advertising and promotion efficiency and human capital performance. Furthermore, we analyze whether the contextual variable of market concentration moderates these two effects (Anderson, Fornell, and Mazvancheryl 2004).

In addition to closing a gap in the literature, studying these two potential outcomes of customer satisfaction is consistent with the proposed research directions of Oliver (1999), who calls for further investigations of the cost effects of customer satisfaction and its potential effects on employees. From a methodological point of view, the current study has two distinctive features. First, it is based entirely on secondary data merged from different archival sources. Second, it offers a dynamic analysis in a longitudinal design. Before presenting the data and the results, we develop the underlying hypotheses.

Hypotheses Development

Can Customer Satisfaction Affect Future Advertising and Promotion Efficiency?

We first address the suggested effects of customer satisfaction on advertising and promotion efficiency. We define the dependent variable, advertising and promotion efficiency, as the optimized conversion ratio of a firm's marketing costs (advertising and promotion investments) to its sales performance, or the firm's deployment ability to convert marketing communications costs into results (Bucklin 1978; Luo and Donthu 2006; Vorhies and Morgan 2003). It is a measure of a firm's marketing productivity (Rust et al. 2004) and an important marketing dashboard metric.

We expect that customer satisfaction induces behaviors (free advertising, loyalty, willingness to pay) that should help the firm become more efficient in its future communication activities. For example, better customer satisfaction can lead to positive word-of-mouth communication, which is free advertising for the firm (see Brown et al. 2005; Ranaweera and Prabhu 2003; Szymanski and Henard 2001), and free advertising reduces the necessity for the company to conduct expensive communication programs to attract new customers. Thus, for a given sales level, marketing costs would be reduced when there is higher customer satisfaction. Perhaps more obvious is the opposite case in which dissatisfied customers give negative references (Blodgett, Wakefield, and Barnes 1995; Bolfing 1989; Fornell et al. 1996; Richins 1983; Szymanski and Henard 2001), and this possibly occurs even to a greater extent than positive word of mouth from satisfied customers (Technical Assistance Research Program 1981). Such negative publicity can be mitigated only by significant advertising and promotion investments, thus harming communication efficiency.

In addition, for a given level of marketing communications costs, customer satisfaction can lead to higher sales performance through improved customer loyalty. As Figure 1 shows, there is extensive evidence that customer satisfaction is an important predictor of customer loyalty (Fornell 1992; Gustafsson, Johnson, and Roos 2005; Liang and Wang 2004; Rust and Zahorik 1993). Previous research has suggested that customer satisfaction and the resultant loyal customer base ensure future sales through consequential purchases and an increased share of wallet (Keiningham, Munn, and Evans 2003; Olsen 2002). Furthermore, customer satisfaction can lead to lower advertising and transaction costs because it is cheaper to retain and serve loyal customers than to acquire new customers (Fornell 1992).

Recent empirical research has also shown that satisfied customers are less price sensitive (Stock 2005) and willing to pay a higher price premium (Homburg, Koschate, and Hoyer 2005). By virtue of premium prices and customer loyalty, we believe that a company with satisfied customers can obtain higher revenues from its existing customers and reduce its dependence on costly marketing communications programs, thus improving its advertising and promotion efficiency. This discussion suggests that customer satisfaction generates more future sales at a given level of advertising and promotion costs or saves future communication costs at a given level of sales. Thus:

> H_1: Customer satisfaction has a positive influence on a company's future advertising and promotion efficiency.

Can Customer Satisfaction Affect Future Human Capital Performance?

Human capital is derived from various sources, such as a person's education, experience, talents, and attitude toward life and business (Hudson 1993). In the firm context, human capital comprises the skills, abilities, knowledge, and experience of people the company employs (Becker 1964; Hitt et al. 2001). Human resources studies have found that various types of human capital (e.g., general employees' human capital, top executives' human capital) are important for increasing company profitability (Benson, Finegold, and Mohrman 2004; Hauser and Simester 1996). Thus, we refer to a company's human capital performance as its excellence in terms of employee talent and managerial superiority compared with its leading rival firms in the industry (based on large-scale surveys, as we detail subsequently). In other words, a firm's human capital performance indicates the employer's ability to attract and keep good people. Research in strategy and marketing suggests that better employee attitude and commitment determine customer service quality and, through improved service quality, drive customer satisfaction (e.g., Hartline and Ferrell 1996; Heskett et al. 1994; Homburg and Stock 2004; Schlesinger and Zornitsky 1991; Tornow and Wiley 1991). Not conflicting with these studies that examine employee attitude, we argue for an ignored impact direction; that is, customer satisfaction drives the firm's human capital performance over time.

In particular, we expect that a firm's customer satisfaction positively affects its future human capital performance for several reasons (e.g., signaling future profitability and emotional contagion). First, there are some financially oriented arguments for the positive impact of customer satisfaction on human capital performance. Given the positive connection between a firm's customer satisfaction and financial performance (e.g., Anderson, Fornell, and Lehmann 1994; Anderson, Fornell, and Mazvancheryl 2004), firms with high customer satisfaction should be able to provide more attractive future financial rewards to their employees. This would prevent good employees from leaving the company and thus contribute to the firm's future human capital performance. Indeed, by signaling and indicating a company's future profitability growth and financial success (Fornell et al. 2006; Gruca and Rego 2005; Luo and Bhattacharya 2006), customer satisfaction promotes a firm's attractiveness to highly qualified potential employees and executives. This signaling effect is particularly relevant in times when customer satisfaction surveys are increasingly circulated and popularized in the media (see Spencer and Albergott 2004; Young 2006). In addition, superior customer satisfaction signals better chances to develop careers and achieve high future salaries and thus augments the firm's attractiveness as an employer. Therefore, firms with high levels of customer satisfaction are able to choose new employees from a broader set of applicants, which again increases the firm's future human capital performance (e.g., Bretz, Boudrau, and Judge 1994; Gatewood, Gowan, and Lautenschlager 1993; Jurgensen 1978).

Second, we rely on the theoretical concept of emotional contagion (see Hatfield, Caccioppo, and Rapson 1994). In particular, the theory of emotional contagion holds that exposure to a person who expresses positive or negative emotions can produce a corresponding change in the observer's emotional state (Pugh 2001). Thus, firm employees (e.g., service employees, salespeople, sales support personnel) who are confronted with highly satisfied customers will develop a higher level of future job satisfaction than employees of firms with frustrated customers who are not satisfied and actively complain (Bearden and Teel 1983; Ping 1993). Higher employee satisfaction then boosts employee loyalty and weakens the likelihood of employee turnover (Fornell 1992). This emotional contagion effect between customer satisfaction and employee satisfaction holds for both services and goods sectors, as long as there is personal interaction between a firm's employees and its customers (Hatfield, Caccioppo, and Rapson 1994). Indeed, in the business-to-business context, and especially for the pharmaceutical, computer, and other high-tech goods sectors, a lot of personal interaction occurs between company employees and customers (Fornell 1992; Harter, Hayes, and Schmidt 2002). Empirically, Ryan, Schmit, and Johnson (1996) find that customer satisfaction has a positive impact on employee satisfaction over time. Echoing this, Harter, Hayes, and Schmidt's (2002) meta-analysis reveals that employee satisfaction is positively related to employee productivity. Moreover, Reichheld's (1996, p. 12) managerially oriented study explicitly states that "the best employees prefer to work for those companies who achieve [customer satisfaction and] customer loyalty." This directly supports the notion that customer satisfaction helps enhance employee performance. Thus:

> H_2: Customer satisfaction has a positive influence on a company's future human capital performance.

The Moderating Role of Market Concentration

Our study also addresses potential moderating effects of market concentration. Market concentration, which can be described as the extent to which a smaller number of supplier firms account for a large proportion of market output, is an important characteristic of market structure that influences several company and market variables. It has been shown that market concentration can significantly affect relationships between customer satisfaction and firm performance outcomes (e.g., Anderson, Fornell, and Mazvancheryl 2004). Indeed, economic theory suggests that there is a close relationship between market concentration and competitive intensity. That is, higher market concentration goes hand in hand with a lower level of competitive intensity (Gatignon, Weitz, and Bansal 1990; Steenkamp et al. 2005).

We believe that customer satisfaction's influence on future advertising and promotion efficiency is more salient in markets with a high concentration than in those with a low concentration. This is because in less-concentrated (and, therefore, more competitive) markets (Gatignon, Weitz, and Bansal 1990; Kim and Lim 1988), even highly satisfied customers are difficult to retain and are more price sensitive, which reduces the likelihood of subsequent purchases and of gaining price premiums (Anderson 1998; Bolton 1998; LaBarbera and Mazursky 1983; Oliver 1999; Seiders et al. 2005). In this case, customer satisfaction is less likely to translate into higher future sales at a given level of advertising and promotion costs. On the contrary, in highly concentrated markets, it is easier for customers to overlook different competitors' offers (Park, Lennon, and Stoel 2005), and in turn, this should lower customers' perceived risk (e.g., the risk of buying a suboptimal product). Given that lowered perceived risk promotes buying intentions and loyalty (Wood and Scheer 1996), we expect that customer satisfaction is more likely to translate into higher future sales at a given level of advertising and promotion cost in highly concentrated markets than in less-concentrated markets. Thus:

> H_3: Customer satisfaction has a stronger influence on a company's future advertising and promotion efficiency in markets with a high concentration than in markets with a low concentration.

We also argue that customer satisfaction should have a stronger effect on human capital performance in markets with a low market concentration than in markets with a high concentration because in markets with a low concentration (and intensive competition), there is an increased necessity for firms to communicate customer satisfaction results to the public. Market competition both motivates and rewards companies to publicize their superior satisfaction rankings (to signal their financial health and future perspectives; see Anderson 1998; Schultz 1961). Indeed, the more markets that are competitive, less concentrated, and highly uncertain, the more likely are talented job applicants to regard customer satisfaction publications as signals of a firm's financial strength and overall attractiveness. In other words, in markets with a low concentration as opposed to markets with a high concentration, more experienced applicants' evaluations of a company's promotion and income opportunities might depend on its customer satisfaction figures.

Furthermore, our hypothesis can be supported through arguments that focus on existing employees and managers. Previous research indicates that in more competitive markets, there is a tendency for higher management turnover (Fee and Hadlock 2002). In this context, a high level of customer satisfaction and the resultant financial performance may be particularly relevant barriers to management turnover and promote the loyalty of highly skilled executives. The resultant decreased risk of the loss of talented employees and managers enables customer satisfaction to have a stronger effect on future human capital performance in markets with a low level of market concentration than in markets with a high level of concentration. Thus:

> H_4: Customer satisfaction has a stronger influence on a company's future human capital performance in markets with a low concentration than in markets with a high concentration.

Data and Method

We collected a large-scale longitudinal data set from multiple archival sources to test the hypotheses. The data have measures for customer satisfaction, advertising and promotion efficiency, and human capital performance. We used data from the annual American Customer Satisfaction Index (ACSI) to gauge customer satisfaction, Competitive Media Reporting (CMR) and COMPUSTAT to derive a measure of advertising and promotion efficiency based on data envelopment analysis (DEA), and *Fortune*'s America's Most Admired Corporations (AMAC) to measure human capital. Table 1 reports the measures and their sources.

Customer Satisfaction

For customer satisfaction, we used survey data from the ACSI. This index provides a customer-based (not an expert-based) measure of overall satisfaction at the firm level. It is designed to represent the health of the national economy as a whole, and it covers all major economic sectors, such as manufacturing durables and nondurables, transportation, communications, utilities, retail, finance, and insurance, among others. It represents approximately 43% of the U.S. economy (Anderson, Fornell, and Mazvancheryl 2004; Fornell et al. 1996).

In compiling this data, ACSI interviews more than 200 customers on average per firm for approximately 200 large companies. More than 65,000 consumers are identified and interviewed annually. Interviewees are from 48 replicate samples of households with telephone services and Internet samples for e-companies. Each respondent (a real user of the products/services) must pass screening questions related to predefined purchase and consumption periods before participating in the survey. The survey questionnaire has multi-

TABLE 1
Measures and Data Sources

Measure	Operationalization	Data Sources	Rationale for Inclusion in Model
Customer satisfaction	The ACSI by the National Quality Research Center (customer-based, independent, cumulative, firm-level satisfaction measure for approximately 200 of *Fortune*'s largest companies in 20 industries and seven sectors in the United States)	ACSI	Independent variable
Advertising and promotion efficiency	A ratio of output (sales volume and sales growth) to inputs (broadcast advertising investment, print advertising investment, outdoor advertising investment, and sales promotion investment)	COMPUSTAT and CMR	Dependent variable
Human capital of employee talent	Employee talent in work-related skills, knowledge, experience, and human resources among 1000 of the largest firms in the United States (the AMAC annual survey)	AMAC	Dependent variable
Human capital of manager superiority	Senior management quality in work-related skills, knowledge, experience, and human resources among 1000 of the largest firms in the United States (the AMAC annual survey)	AMAC	Dependent variable
Market concentration	Herfindahl concentration index in the market	COMPUSTAT	Moderating variable

ple items for multiple constructs that are used to estimate the latent variable of overall customer satisfaction. The resultant customer satisfaction for an individual firm indicates its served customers' overall evaluation of total consumption experiences. This measure ranges from 0 to 100 (the highest).

The ACSI data set offers a unique and reliable measure of customer satisfaction because it employs identical survey methods, interview procedures, sampling, and estimation methods across firms and years. A comprehensive test of the validity and reliability of this satisfaction measure can be found in the work of Fornell and colleagues (1996). An emerging and growing body of literature has successfully employed this satisfaction database (e.g., Anderson, Fornell, and Mazvancheryl 2004; Fornell et al. 2006; Gruca and Rego 2005; Mithas, Krishnan, and Fornell 2005; Mittal et al. 2005; Morgan and Rego 2006). We were able to collect this survey-based measure of customer satisfaction for 139 companies in 2002 (Time 1) and 2003 (Time 2).

Although the total sample size of the ACSI for the two years is more than 139 companies and comprises approximately 200 firms/brands, we were not able to obtain a larger sample size for the final merged data set for several reasons. The sampled firms in the ACSI have changed over the years, and the ACSI methodology has incorporated more and more companies, from fewer than 130 firms/brands to more than 200 firms/brands. For example, customer satisfaction scores of some companies/brands (e.g., CenterPoint Energy Inc., Pepco Holdings Inc., Verizon Wireless, Kohl's Corporation, Orbitz Inc.) are not measured until 2005. Furthermore, in the ACSI, the same corporation may have multiple brands. For example, General Motors has Cadillac, Buick, Saturn, GMC, Pontiac, and Chevrolet brand-level customer satisfaction scores. Thus, following prior studies (i.e., Anderson, Fornell, and Mazvancheryl 2004, p. 177), we aggregated these multibrands at the firm level. After this step, we merged the ACSI data with other secondary sources, such as the AMAC, CMR, and COMPUSTAT at the firm, not the brand, level for the 278 firm-year unbalanced panel observations (278 = 139 firms × 2 years). To fill in the missing data, we also extensively searched other secondary sources, such as company annual reports, Standard & Poor's industry reports, Moody's reports, and Compact Disclosure. This merged data set includes individual firms in various industries, such as airlines, athletic shoes, automobiles, department and discount stores, hotels, household appliances, personal computers, supermarkets, and utilities. Table 2 reports descriptive statistics and correlations of customer satisfaction and other variables.

Advertising and Promotion Efficiency

We measured advertising and promotion efficiency with the DEA approach. Developed by operations research scholars (Banker, Charnes, and Cooper 1984; Charnes, Cooper, and Rhodes 1978), DEA is a mathematical programming technique that assesses the efficiency of resource utilization. Luo (2004) provides a comprehensive review of DEA applications in consumer research, advertising, retailing, and personal selling, among other areas.

Essentially, DEA measures the relative efficiency of a firm in converting multiple inputs into multiple outputs. The efficiency of a particular company is the conversion ratio of producing the outputs from the necessary inputs compared with best practices of competing firms. In DEA modeling, a firm is efficient (conversion ratio = 100%) if it cannot reduce its investments in any inputs while holding the same levels of outputs (or cannot increase its outputs while hold-

TABLE 2
Descriptive Statistics and Correlations

Variables	M	SD	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1: Customer satisfaction (Time 1)	75.24	6.94	1.00											
V2: Human capital of employee talent (Time 1)	5.80	1.21	.16	1.00										
V3: Human capital of manager superiority (Time 1)	6.13	1.27	.17	.85***	1.00									
V4: Advertising and promotion efficiency (Time 1)	.61	.28	.14	.11	.14	1.00								
V5: Human capital of employee talent (Time 2)	6.02	1.14	.22**	.81***	.77***	.12	1.00							
V6: Human capital of manager superiority (Time 2)	6.41	1.20	.20*	.77***	.80***	.14	.81***	1.00						
V7: Advertising and promotion efficiency (Time 2)	.68	.30	.25**	.13	.12	.42***	.12	.10	1.00					
V8: Market concentration (Time 1)	.21	.13	.09	.06	.08	.03	.03	.02	.05	1.00				
V9: Business segments (Time 1)	2.36	1.85	.03	.01	.02	–.03	.00	.01	–.01	–.04	1.00			
V10: Firm size (Time 1)	4.11	.93	.02	–.01	–.00	–.02	.01	–.01	–.00	–.02	.05	1.00		
V11: Operating leverage (Time 1)	.37	.58	–.03	–.04	–.02	–.03	–.01	–.02	.18*	.01	.02	–.03	1.00	
V12: Financial leverage (Time 1)	2.03	7.11	–.04	.01	.02	.04	.17*	.03	.04	–.03	.05	.01	–.02	1.00

*$p < .10$.
**$p < .05$.
***$p < .01$.

ing the same levels of inputs). Otherwise, a firm is not efficient, and the portion of inputs and costs (1 – conversion ratio) is what can be saved while achieving the same level of outputs for the firm.

There are two key advantages of the DEA approach to modeling efficiency over traditional simple ratios (output/input). First, DEA results are based on comparisons with the most efficient firms that operate under similar situations and scales, whereas simple ratios reflect average performing firms and do not account for firm heterogeneity. Second, DEA is a mathematical programming that does not require any subjective specifications in weighting the multiple inputs and multiple outputs, whereas simple ratios require such a subjective assumption (Charnes, Cooper, and Rhodes 1978; Luo and Donthu 2006).

To model advertising and promotion efficiency with DEA, we used four inputs: broadcast advertising investment (BAI), print advertising investment (PAI), outdoor advertising investment (OAI), and sales promotion investment (SPI). These different kinds of spending are the firm's marketing communications mix efforts. We obtained the data on these advertising and promotion inputs from CMR. The output variables in DEA are sales volume (SAL) and sales growth (SGO).[1] We gleaned data on sales volume and growth from COMPUSTAT. Next, we present the DEA model, in which advertising and promotion efficiency is expressed as ψ, a conversion ratio of output to inputs:

$$\psi = \frac{\text{Outputs}}{\text{Inputs}}. \tag{1}$$

We can obtain the advertising and promotion efficiency for firm w by solving the subsequent fractional programming format (Charnes, Cooper, and Rhodes 1978). The objective of this programming model is to maximize this conversion ratio for firm w by fitting the data with different weights for outputs (u1 and u2) and inputs (v1, v2, v3, and v4). The constraint of these weights ensures that the resultant advertising and sales promotion efficiency is optimized for firm w in the estimation:[2]

$$\text{Max } \psi_w = \frac{u1 \times SAL_w + u2 \times SGO_w}{v1 \times BAI_w + v2 \times PAI_w + v3 \times OAI_w + v4 \times SPI_w}, \tag{2}$$

subject to

$$\frac{u1 \times SAL_k + u2 \times SGO_k}{v1 \times BAI_k + v2 \times PAI_k + v3 \times OAI_k + v4 \times SPI_k} \leq 1,$$

$$(k = 1, 2, \ldots, n),$$

$$u1, u2, v1, v2, v3, v4 \geq 0.$$

All estimated efficiency (ψ_w) results are either equal to or less than 1 (100%) because firm w is enveloped by the efficient frontier with all firms (including itself) in DEA programming. The most efficient firms (identified as the best practices by DEA) have a value of 1 for the efficiency, and the remaining firms have a value between 0 and 1. The portion ($1 - \psi_w$) represents the inefficient percentage of advertising and sales promotion investments for firm w. In our analyses, the mean of advertising and promotion efficiency was .61 (SD = .28) for Time 1 and .68 (SD = .30) for Time 2 (see Table 2).

Human Capital Performance

To measure human capital performance, objective firm data can be used. For example, company-specific human capital can be measured with firm records on employee enrollment and the types of degrees employees earned as a result of company tuition reimbursement (Benson, Finegold, and Mohrman 2004). In addition, human capital at the top manager level can be assessed by company records on chief executive officer success, tenure, and age (Buchholtz, Ribbens, and Houle 2003). However, company records of this type have inherent limitations: (1) The records may not be exhaustive, and thus it is difficult to check their validity, which leads to a concern of biased findings, and (2) these

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[1] We conducted additional analyses with profit and found that the DEA results are robust and stable. Specifically, we reran DEA models with different combinations of outputs across DEA1 (sales, sales growth), DEA2 (sales, sales growth, profit), DEA3 (sales, profit), and DEA4 (sales growth, profit). We defined profit as the net incomes before extraordinary items (Chauvin and Hirschey 1993; Erickson and Jacobson 1992). The correlation results between DEA1 and DEA2 was .86, the correlation between DEA1 and DEA3 was .88, and the correlation between DEA1 and DEA4 was .86. These sensitivity results seem to support the robustness of the DEA results. Thus, we now add a brief new table.

DEA Sensitivity Results for Adverting and Promotion Efficiency

Model Specifications	Correlations	*p* Value
DEA1 (sales, sales growth) vs. DEA2 (sales, sales growth,	.86	$p < .01$
DEA1 (sales, sales growth) vs. DEA3 (sales, profit)	.88	$p < .01$
DEA1 (sales, sales growth) vs. DEA4 (sale growth, profit)	.86	$p < .01$

[2] We also considered the lagged impact of advertising and promotion on sales. Specifically, before DEA analysis, our measure of sales level ($\text{SALES}_t{}^{\sim}$) already controlled the carryover effects of advertising (i.e., Chauvin and Hirschey 1993; Vakratsas and Ambler 1999) and the impact of other relevant factors, such as research and development and firm size, as well as the industry level factors (i.e., industry concentration). In addition, solving the fractional programming requires some mathematical manipulations. We can derive this with the following linear programming model:

$$\text{Max } \psi_w = q1 \times SALw + q2 \times SGOw,$$

$$\text{subject to } p1 \times BAIw + p2 \times PAIw + p3 \times OAIw$$
$$+ p4 \times SPIw = 1,$$
$$q1 \times SALk + q2 \times SGOk \leq p1 \times BAIk$$
$$+ p2 \times PAIk + p3 \times OAIk + p4 \times SPIk,$$

where k = 1, 2, ..., n.

company records are neither large scale in terms of the number of firms involved nor comparable across firms because of different booking and housekeeping practices (Davenport and Prusak 1988). Thus, we used the comprehensive longitudinal survey data for measuring human capital from the AMAC.

In particular, the AMAC provides two types of human capital performance: employee talent and manager superiority. For Time 1 and Time 2, the AMAC has data on more than 10,000 senior executives, outside directors, and industry analysts from more than 580 large companies (e.g., Fombrun and Shanley 1990; *Fortune* 2005, p. 68) across 70 major industries. Companies are required to have at least $1.3 billion in revenue to be eligible for the sampling list. For companies on the AMAC list, a maximum of ten top executives and seven directors (outside board members) per company are selected, as well as a pool of industry analysts. The AMAC surveys the respondents' perceptions of a firm's excellence in terms of its employee talent and quality of management compared with that of the major competing companies in the industry. The attributes of human capital performance are defined on the AMAC survey as "the ability to attract and retain talented people" and "quality of management."

The AMAC items of human capital performance are derived from a series of interviews and pilot tests with a large pool of executives and industry analysts. The AMAC compiles the list of these respondents in August and sends out the surveys in October with a follow-up reminder mailing in November. At the latest, all surveys are due by mid-December. The score of these human capital performance measures ranges from 0 to 10 (the highest).

Prior studies (e.g., Fombrun and Shanley 1990; Houston and Johnson 2000; McGuire, Schneeweis, and Branch 1990) have reported evidence of the internal consistency and validity of these data. In particular, McGuire, Schneeweis, and Branch (1990, p. 170) note that it may be "one of the most comprehensive and widely circulated surveys of attributes available. Both the quality and number of respondents are comparable or superior to the 'expert panels' usually gathered for such purposes." However, because the AMAC data have strong halo effects with firm financial performance, we parceled out this bias by using the approach (e.g., Roberts and Dowling 2002) for both employee talent and manager superiority. Specifically, we regressed human capital measures (employee talent and managerial superiority) against firm financial performance (return on assets) in the prior four years and saved the residual of this regression as the final measure of human capital. Because this residual is independent from financial performance, the reverse causality bias and halo effects in measuring human capital are parceled out.

Market Concentration and Controls

We measured market concentration intensity using the Herfindahl concentration index. We derived this measure on the basis of the lagged sales for all the companies with the North American Industry Classification System four-digit codes for each firm-year observation (Anderson, Fornell, and Mazvancheryl 2004; Rao, Agarwal, and Dahlhoff 2004). We obtained data for all control variables from the COMPUSTAT database. In particular, we controlled for firm size, which is the log of the number of employees. Operating leverage is the ratio of fixed assets to total assets. Financial leverage refers to the ratio of book debt to total assets (Rao, Agarwal, and Dahlhoff 2004). Finally, business segment is the number of segments in which the firm operates in the marketplace (Rao, Agarwal, and Dahlhoff 2004).

Analyses and Results

Analyzing the data requires estimation techniques that can accommodate the unique distribution of advertising and promotion efficiency results. In addition, such techniques should consider the correlated error terms in a series of regression equations that involve two types of human capital performance.

Advertising and Promotion Efficiency Results

Because DEA-based advertising and promotion efficiency results are censored with an upper bound of 1 and a lower bound of 0, traditional ordinary least squares cannot parcel out this sample censoring bias. As a result, we employ the two-limit Tobit model (Heckman 1979). Datar and colleagues (1997) apply this type of Tobit modeling in their investigation of time-based new product development. Let $y_{t2,i}{}^*$ denote the latent advertising and promotion efficiency of firm i at Time 2, $X_{t1,i}$ denote a vector of explanatory variables at Time 1, and β denote a vector of coefficients. Then, the advertising and promotion efficiency of firm i is given by

$$
\begin{aligned}
(3)\quad y_{t2,i}{}^* = X_{t1,i}\,\beta + \varepsilon_i = \beta_0 &+ \beta_1 \mathrm{CustomerSatisfaction}_{t1,i}\\
&+ \beta_2 \mathrm{MarketConcentration}_{t1,i}\\
&+ \beta_3 \mathrm{CustomerSatisfaction}_{t1,i} \times \mathrm{MarketConcentration}_{t1,i}\\
&+ \beta_4 \mathrm{BusinessSegments}_{t1,i} + \beta_5 \mathrm{FirmSize}_{t1,i}\\
&+ \beta_6 \mathrm{OperationLeverage}_{t1,i} + \beta_7 \mathrm{FinancialLeverage}_{t1,i}\\
&+ \beta_8 y_{t1,i} + \varepsilon_i,
\end{aligned}
$$

where ε_i denotes the normally distributed residuals with a zero mean and a σ^2 variance. However, because the dependent variable of advertising and promotion efficiency ranges from 0 to 1, we control for this sample censoring and specify the observed advertising and promotion efficiency (y_i):

$$
\begin{aligned}
(4)\qquad & y_{t2,i} = 0 && \text{if } y_{t2,i}{}^* \leq 0 \text{ (lower bound),}\\
& y_{t2,i} = y_{t2,i}{}^* && \text{if } 0 < y_{t2,i}{}^* < 1, \text{ and}\\
& y_{t2,i} = 1 && \text{if } y_{t2,i}{}^* \geq 1 \text{ (upper bound).}
\end{aligned}
$$

The log-likelihood function is specified as

$$
\begin{aligned}
(5)\quad l(\beta, \sigma) = \sum_{i=1}^{N} &\log f\left[(y_{t2,i} - x'_{t1,i}\beta)/\sigma\right] \times 1(\underline{c}_i < y_{t2,i} < \overline{c}_i)\\
&- \log\left\{F\left[(\overline{c}_i - x'_{t1,i}\beta)/\sigma\right] - F\left[(\underline{c}_i - x'_{t1,i}\beta)/\sigma\right]\right\}, \ (\underline{c}_i = 0,\ \overline{c}_i = 1).
\end{aligned}
$$

The impact of customer satisfaction on advertising and promotion efficiency. In H_1, we predict that there is a positive impact of customer satisfaction on future advertising and promotion efficiency. As Table 3 reports, the Tobit modeling results indicate that customer satisfaction at Time 1 is positively and significantly related to advertising and promotion efficiency at Time 2 ($b = .29, p < .05$). Therefore, the data support H_1.

The moderating role of market concentration. In H_3, we expect that the positive impact of customer satisfaction on advertising and promotion efficiency is expanded under conditions of high market concentration. To test this, we mean-centered customer satisfaction and market concentration before generating the interaction term (Aiken and West 1991). The Tobit results suggest that the interaction between customer satisfaction and market concentration has a positive and marginally significant influence on advertising and promotion efficiency at Time 2 ($b = .21, p < .05$). Because the highest variance inflation factor was 2.80, the threat of multicollinearity bias was not severe. We plot the data to facilitate the interpretation of these moderating effects. Figure 2 illustrates the impact of customer satisfaction on advertising and promotion efficiency for low versus high market concentration (see Aiken and West 1991, pp. 12–14). Figure 2 shows that the positive influence of higher customer satisfaction at Time 1 on advertising and promotion efficiency at Time 2 is more salient in markets with a high concentration than in markets with a low concentration. Thus, the data support H_3.

Human Capital Performance Results

To test the impact of customer satisfaction on two dimensions of human capital performance, we specify a series of regression equations. Let $y1_{t2,i}$ denote the human capital of employee talent and $y2_{t2,i}$ denote the human capital of manager superiority at Time 2:

$$
\begin{aligned}
(6)\quad y1_{t2,i} = X_i\gamma + \varepsilon 1_i = {} & \gamma_0 + \gamma_1 \text{CustomerSatisfaction}_{t1,i} \\
& + \gamma_2 \text{MarketConcentration}_{t1,i} \\
& + \gamma_3 \text{CustomerSatisfaction}_{t1,i} \times \text{MarketConcentration}_{t1,i} \\
& + \gamma_4 \text{BusinessSegments}_{t1,i} + \gamma_5 \text{FirmSize}_{t1,i} \\
& + \gamma_6 \text{OperationLeverage}_{t1,i} + \gamma_7 \text{FinancialLeverage}_{t1,i} \\
& + \gamma_8 y1_{t1,i} + \varepsilon 1_i, \text{ and}
\end{aligned}
$$

$$
\begin{aligned}
y2_{t2,i} = X_i\delta + \varepsilon 2_i = {} & \delta_0 + \delta_1 \text{CustomerSatisfaction}_{t1,i} \\
& + \delta_2 \text{MarketConcentration}_{t1,i} \\
& + \delta_3 \text{CustomerSatisfaction}_{t1,i} \times \text{MarketConcentration}_{t1,i} \\
& + \delta_4 \text{BusinessSegments}_{t1,i} + \delta_5 \text{FirmSize}_{t1,i} \\
& + \delta_6 \text{OperationLeverage}_{t1,i} + \delta_7 \text{FinancialLeverage}_{t1,i} \\
& + \delta_8 y2_{t1,i} + \varepsilon 2_i.
\end{aligned}
$$

Because the error terms ($\varepsilon 1$, $\varepsilon 2$) can be correlated and the dependent variables of the two dimensions of human capital are also correlated, we employed the seemingly unrelated regression (SUR) estimation technique (Zellner 1962). In this situation, SUR will produce more robust coefficients than the traditional ordinary least squares technique.

The impact of customer satisfaction on human capital performance. In H_2, we predict that there is a positive impact of customer satisfaction on future human capital performance. As Table 4 reports, the SUR modeling results indicate that customer satisfaction at Time 1 has a positive, significant influence on human capital performance in terms of both employee talent and manager superiority at Time 2 ($b = .33, p < .01$, and $b = .27, p < .05$, respectively). Thus, the data strongly support H_2.

The moderating role of market concentration. In H_4, we expect that the positive impact of customer satisfaction on

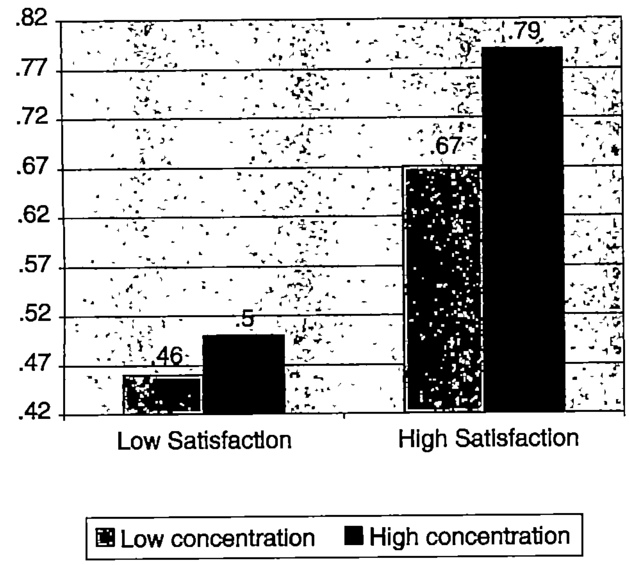
TABLE 3
Impact of Customer Satisfaction on Future Advertising and Promotion Efficiency: Tobit Results

Independent Variables (Time 1)	Advertising and Promotion Efficiency (Time 2) Prediction	Estimate	*p* Value	Unobserved Heterogeneity	Support for Hypotheses
Customer satisfaction	H_1 +	.29	.02 (one-tailed)	.05 (n.s.)	H_1 supported
Market concentration		.05	.46	–.01 (n.s.)	
Customer satisfaction × market concentration	H_3 +	.21	.03 (one-tailed)	.02 (n.s.)	H_3 supported
Business segments		–.07	38	–.02 (n.s.)	
Firm size		.05	.41	.03 (n.s.)	
Operating leverage		.18	.05 (one-tailed)	.06 (n.s.)	
Financial leverage		.09	.35	.01 (n.s.)	
Advertising and promotion efficiency		.45	.00	.09 ($p < .05$)	

Notes: Because advertising and promotion efficiency results are truncated values with censored distribution based on linear programming modeling, we used Tobit regression to test the hypotheses. We estimated random unobserved heterogeneity models to test the robustness of the results. Schwartz Bayesian information criterion = 472.50, and Akaike's information criterion = 463.77. The reported results in the "Unobserved Heterogeneity" column are the difference between random coefficient model (RCM) coefficients and non-RCM coefficients. The results of n.s. mean that there is no significant cross-modeling (RCM or not) variation in the database.

FIGURE 2

The Moderating Role of Market Concentration on the Impact of Customer Satisfaction (Time 1) on Future Advertising and Promotion Efficiency (Time 2)



human capital performance is reduced under conditions of high market concentration. The results suggest that the interaction between customer satisfaction and market concentration has a negative, significant influence on human capital in terms of employee talent at Time 2 ($b = -.21$, $p < .05$) and on human capital in terms of manager superiority ($b = -.18$, $p < .10$). Thus, the data support H_4.

Additional Data Analysis

We specified several alternative models and tested competing explanations of the results. First, we examined the reverse-causality concern by conducting Granger (1969) causality tests (see also Chintagunta and Haldar 1998; Hidalgo 2005).[3] In this context, we computed the following Wald F tests: The F statistics account for 7.38 ($p < .01$) of the influence of customer satisfaction on advertising and promotion efficiency, 6.73 ($p < .01$) of the impact of customer satisfaction on human capital performance in terms of employee talent, and 6.01 ($p < .01$) of the influence of customer satisfaction on human capital performance in terms of manager superiority. This means that customer satisfaction Granger causes advertising and promotion efficiency, employee talent, and manager superiority. Moreover, the F statistics account for 1.50 ($p > .05$) of the influence of advertising and promotion efficiency on customer satisfaction, .77 ($p > .05$) of the impact of human capital performance on customer satisfaction in terms of employee talent, and .92 ($p > .05$) of the influence of human capital performance on customer satisfaction in terms of manager superiority. This means that advertising and promotion efficiency, employee talent, and manager superiority do not Granger cause customer satisfaction in this sample. Overall, these Granger causality test results seem to support our theoretical framework on the neglected outcomes of customer satisfaction.

Second, we estimated rival models with the terms of customer satisfaction squared and cubed (i.e., for competing explanations in terms of nonlinear impact). We failed to find these higher-order terms significant in either Tobit or SUR estimations ($p > .10$), but the first-order term of customer satisfaction and the interaction term between customer satisfaction and market concentration remained significant ($p < .05$).

Third, we employed random coefficient models (RCMs) to test the results' robustness. As we report in the "Unobserved Heterogeneity" columns in Table 3 and Table 4, none of the estimated RCM results are significantly ($p > .05$) different from non-RCM coefficients. This means that there is no significant cross-modeling (RCM or not) variation. In this sense, our findings are stable and robust.

Fourth, the analysis of time-series cross-sectional data can suffer from both autocorrelation and heteroskedasticity bias (thus varying and heterogeneous estimators). As a result, we conducted more sensitivity analyses with general method of moments (GMM) estimation. The GMM estimation approach does not require full density and can accommodate possible autocorrelation bias and generate het-

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[3] The model for testing the Granger causality between customer satisfaction and advertising and promotion efficiency is specified as follows:

$$\text{AdvertisingPromotionEfficiency}_t = \pi_1\text{AdvertisingPromotionEfficiency}_{t-1} + \chi_1\text{CustomerSatisfaction}_t + \chi_2\text{CustomerSatisfaction}_{t-1} + \upsilon_t,$$

$$\text{CustomerSatisfaction}_t = \phi_1\text{AdvertisingPromotionEfficiency}_t + \phi_2\text{AdvertisingPromotionEfficiency}_{t-1} + \omega_1\text{CustomerSatisfaction}_{t-1} + \tau_t.$$

In these equations, if all the coefficients are significant, advertising and promotion efficiency and customer satisfaction mutually lead to (Granger cause) each other. If only the coefficients of χ_j are significant, customer satisfaction Granger causes advertising and promotion efficiency. If only the coefficients of ϕ_j are significant, advertising and promotion efficiency Granger causes customer satisfaction. A Wald F test determines the significance of the equations. This test statistics is specified as follows:

$$F = \frac{(SSR1 - SSR2)/q}{SSR2/(n - s)},$$

where SSR1 is defined as the sum of squared residuals in the restricted equation (in which χ_j and ϕ_j are restricted to zero) and SSR2 is the sum of squared residuals in the unrestricted equation. In addition, q = the number of restrictions, n = the number of observations, and s = the number of independent variables in the unrestricted equation. The model for testing the Granger causality between customer satisfaction and human capital performance in terms of employee talent and manager superiority requires replacing advertising and promotion efficiency with human capital performance variables.

TABLE 4
Impact of Customer Satisfaction on Future Human Capital Performance: SUR Results

Independent Variables (Time 1)	Human Capital of Employee Talent (Time 2)				Human Capital of Manager Superiority (Time 2)			
	Prediction	Estimate	*p* Value	Unobserved Heterogeneity	Estimate	*p* Value	Unobserved Heterogeneity	Support for Hypotheses
Customer satisfaction	H_2 +	.33	.01 (one-tailed)	.05 (n.s.)	.27	.02 (one-tailed)	.03 (n.s.)	H_2 supported
Market concentration		.06	.70	.04 (n.s.)	.05	.80	.01 (n.s.)	
Customer satisfaction × market concentration	H_4 –	–.21	.04 (one-tailed)	–.01 (n.s.)	–.18	.05 (one-tailed)	–.04 (n.s.)	H_4 supported
Business segments		.02	.94	.03 (n.s.)	.01	.97	.04 (n.s.)	
Firm size		.03	.85	.01 (n.s.)	.02	.91	.01 (n.s.)	
Operating leverage		.12	.22	.02 (n.s.)	.07	.72	.02 (n.s.)	
Financial leverage		.23	.03 (one-tailed)	.04 (n.s.)	.08	.63	.02 (n.s.)	
Human capital of employee talent		.51	.00	.08 ($p < .05$)				
Human capital of manager superiority					.62	.00	.06 (n.s.)	

Notes: Because the error terms can be correlated and the dependent variables of the two dimensions of human capital performance are also correlated, we employed the SUR estimation technique to test the hypotheses. The reported results in the "Unobserved Heterogeneity" columns are the difference between random coefficient model (RCM) coefficients and non-RCM coefficients. The results of n.s. mean that there is no significant cross-modeling (RCM or not) variation in the database.

eroskedasticity consistent results (Hansen 1982; Prabhu, Chandy, and Ellis 2005).[4] The GMM results also show that our conclusion is robust; that is, customer satisfaction leads to greater advertising and promotion efficiency and stronger human capital performance.

Fifth, because DEA mathematical programming is nonparametric in nature and is sensitive to extreme data values and measure errors (Charnes, Cooper, and Rhodes 1978; Luo 2004; Luo and Donthu 2001), it is important to test the robustness of DEA-based advertising and promotion efficiency results. Thus, we repeated the DEA analyses with other combinations of variables (i.e., two outputs and three inputs, one output and four inputs, one output and three inputs). The resultant advertising and promotion efficiency results are significantly correlated (smallest $r = .89$, $p < .01$), attesting to the robustness of the DEA results.

Finally, we explored profitability implications. The results show that advertising and promotion efficiency has a significant impact on Tobin's q ($b = .37$, $p < .01$).[5] In addition, human capital performance in terms of employee talent has a significant impact on Tobin's q ($b = .31$, $p < .01$), and human capital performance in terms of manager superiority has a marginal significant impact on Tobin's q ($b = .17$, $p < .10$ [one-tailed]). We also find that customer satisfaction has a significant impact on Tobin's q ($b = .36$, $p < .01$). This result is consistent with extant studies (Anderson, Fornell, and Mazvancheryl 2004; Fornell et al. 2006; Gruca and Rego 2005).

Discussion

Our study was a result of the further research opportunities provided in the extant academic literature of the performance outcomes of customer satisfaction. After the association between customer satisfaction investments and financial performance is established, it is important to examine the direct linkages through which a firm's financial success is created. We explored two outcomes of customer satisfaction that have not been investigated so far. On the basis of longitudinal analyses with a matched secondary data set from multiple sources, we showed that customer satisfaction not only increases a firm's future advertising and promotion efficiency but enhances its subsequent human capital performance as well.

Managerial Implications

Our study offers some helpful managerial implications. The results of our study suggest that firms with higher levels of customer satisfaction should use this performance metric to attract and retain high-quality employees and managers because such personnel are the fundamentals of a company's human capital excellence (Schultz 1961). Although the use of a customer satisfaction index in personnel recruiting is not yet common in business, this index can be powerful (*Fortune* 2006; Young 2006). The finding of an expanded, positive influence of customer satisfaction on employee talent in less-concentrated markets suggests that firms should (1) proactively publicize their superior satisfaction ratings and (2) extensively use this metric in their human resources recruiting, compensation, and retention programs, especially in less-concentrated markets in which there is fierce competition. Indeed, because customer satisfaction leads to human capital excellence, human resources managers have a good reason to pay attention to the firm's customer satisfaction index.

Furthermore, we suggest that companies should carefully monitor their marketing communications efficiency and relate these analyses to customer satisfaction benchmarks. If a firm with superior customer satisfaction values is not more efficient in terms of marketing communications than its competitors, the firm's communication management has the potential for efficiency improvement. This implication is especially important in industries in which firms spend a considerable percentage of their revenues on marketing communications. Thus, this implication would be more relevant for consumer goods firms than for firms in business-to-business marketing.

With regard to our empirical findings, marketing managers could raise the question whether spending on customer satisfaction is more effective than spending on advertising. From our analyses, we were not able to provide a specific answer to this question, because we had no information about the costs of increasing customer satisfaction. If these costs are extremely high for a firm, the achieved increase in advertising and promotion efficiency may not be able to compensate for these costs. However, if costs of increasing customer satisfaction are fairly low, it may make sense to shift budgets from advertising to customer satisfaction activities. Consequently, we suggest that firms should conduct cost–benefit analyses with their individual data to determine an appropriate marketing budget allocation. In this context, it is also important to mention that our findings show that expenditure on customer satisfaction would lead to saved future advertising money. Because expenditure on advertising is important for current sales, customer/brand equity, and market share (i.e., Mizik and Jacobson 2003), this may limit the possibility to shift expenditures from advertising to customer satisfaction improvement.

---

[4] In particular, in the GMM approach, the White's heteroskedasticity and autocorrelation consistent covariance matrix Ω_{HAC} is

$$\Omega_{HAC} = \Gamma(0) + \left[\sum_{j=1}^{T-1} k(j, q)\Gamma'(j) + \Gamma'(j)\right]$$

and

$$\Gamma(j) = \frac{1}{T-K}\left(\sum_{t=j+1}^{T} Z_{t-j}{}'u_t u_{t-j}{}'Z_t\right),$$

where u is the vector of White errors and Z_t is a $k \times p$ matrix. For a technical discussion of the GMM approach, see Hansen (1982), and for nontechnical prior applications of the GMM in marketing, see Krishnan, Bass, and Kumar (2000), Kim, Allenby, and Rossi (2002), and Prabhu, Chandy, and Ellis (2005).

[5] Tobin's q is defined by following prior literature. Particularly, Rao, Agarwal, and Dahlhoff (2004) provide a detailed function for deriving Tobin's q: q = (share price × number of common stock outstanding + liquidating value of the firm's preferred stock + short-term liabilities – short-term assets + book value of long-term debt)/book value of total assets.

In addition, the results of the study should be valuable for marketing managers in their dialogue with CFOs. Because there is a strong push for marketing accountability in the corporate world (Fornell et al. 2006; Luo and Donthu 2006; Rust, Lemon, and Zeithaml 2004), our finding that customer satisfaction increases advertising and promotion efficiency provides a strong argument. Specifically, customer satisfaction can also help save future marketing money. Thus, marketers should approach top executives and seriously question relentless cost cutting on programs that aim to increase customer satisfaction and loyalty. Indeed, better customer satisfaction may enable the firm to consume fewer resources in the future while achieving better efficiency; that is, improving customer satisfaction helps generate more future sales at a given level of advertising and promotion costs or saves future marketing communications costs at a given level of sales.

Finally, a constant challenge for managers who want to improve marketing accountability is the lack of a scientific measure of efficiency. Our study meets this challenge and informs managers of how DEA can be applied to pulse and improve advertising efficiency. This technique is especially important in consumer goods industries in which firms spend a considerable percentage of their revenues on marketing communications. For example, by using DEA, package goods companies can carefully monitor their marketing communications efficiency and relate these analyses to customer satisfaction benchmarks. Because DEA efficiency results are benchmarked against competitors' best practices rather than against average performers in traditional regression-based approaches, DEA offers a rigorous and scientific method for managers to furnish the marketing metrics dashboard. Indeed, firms can easily employ DEA to measure and boost the efficiencies of marketing activities, such as product development, branding, customer experience management, price promotion, personal selling, and channel governance (Horsky and Nelson 1996; Luo and Donthu 2001, 2006; Murthi, Srinivasan, and Kalyanaram 1996).

Research Issues

We believe that this study contributes to a better understanding of beneficial consequences of customer satisfaction for firms. Previous research has largely focused on effectiveness outcomes, such as customer loyalty, customer retention, and price perceptions (e.g., Anderson and Sullivan 1993; Mittal and Kamakura 2001). To the best of our knowledge, this study is the first to show that customer satisfaction significantly affects efficiency outcomes of advertising and promotion investments. It seems that a high level of customer satisfaction may allow firms to allocate future marketing communications costs more efficiently and productively. Because advertising and promotion efficiency is, by definition, directly linked to a company's profitability, it constitutes a critical marketing metric for future research efforts that address the marketing productivity chain (Rust, Lemon, and Zeithaml 2004). Our finding of the impact of customer satisfaction on communication efficiency helps alleviate the criticism of marketing's lack of accountability because by saving future marketing costs, customer equity building with higher satisfaction and loyalty generates more cash flow and shareholder value (Fornell et al. 2006; Gruca and Rego 2005).

Another key finding of our study is that improving customer satisfaction enables firms to build superior human capital on both the employee and the management level. This result is highly novel and refreshing because previous satisfaction research has focused on customer-related rather than employee-related outcomes. It seems that customer satisfaction may signal that the company has good prospects. In this sense and on a more general level, our work suggests that marketing and strategy research should explore the interface between customer satisfaction and human resources management in greater detail. Further research might extend our efforts and examine a multitude of other interlinked concepts from the two disciplines—for example, relating customer satisfaction to (1) chief executive officer succession, top management compensation, and turnover rate and (2) personnel selection, employee training, and motivation.

Overall, our work contributes to the important literature on customer satisfaction and its intermediate consequences. We call for more research efforts along these lines so that important outcomes (e.g., a firm's future advertising and promotion efficiency and human capital excellence) of customer satisfaction will not be neglected any longer.

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Ashutosh Dixit & Pradeep K. Chintagunta

Learning and Exit Behavior of New Entrant Discount Airlines from City-Pair Markets

In this research, the authors investigate firms' exit behaviors. On the basis of extant literature in economics, strategy, and marketing, the authors identify market- and firm-specific factors that influence exit behavior. They account for firms' uncertainty about a market's true attractiveness after entry on the probability of exiting a market. To evaluate exit decisions, they propose a Bayesian belief-updating model of learning embedded in a logit model that incorporates market- and firm-specific factors. The estimated evolution of beliefs over time enables the authors to determine whether firms use market information to update their prior beliefs about market attractiveness. The authors empirically investigate the market exits of new entrant discount airlines from city-pair markets. The results suggest that a combination of several market and firm factors influences exit behavior. Airlines' prior beliefs about market attractiveness are not necessarily consistent with the market's intrinsic attractiveness, and firms learn about the true market attractiveness over time. The authors also provide model comparisons with extant approaches to studying market exit and find that the proposed approach provides a better fit and predictive ability.

Market entry and exit are important empirical themes in the economics, strategy, and marketing literature. Whereas research on market entry (including firm and product introductions) is abundant, empirical investigations of market exits are relatively rare, though research on exit behavior could lead to useful marketing insights that may prevent future new product failures. Because market exit may be related to the failure of an organization to adapt to its circumstances (Cameron, Sutton, and Whetten 1988; Mellahi and Wilkinson 2004), understanding the factors that underlie market exit is critical for the long-term viability of a firm and its products. Current literature on market exit falls into two research streams: Economics and industrial organization research examines market exit on the basis of macroeconomic, market-related factors, and firm-specific factors, whereas organizational studies, marketing, and strategy research explains market exit using behavioral theories, market uncertainty, and managerial decision-making perspectives.

A key contribution of this research is that we account for the role of firms' learning behaviors on their market exit decisions and incorporate the various market- and firm-specific factors that previous literature has identified as drivers of market exit. Marketing managers make market entry decisions even when the available information is limited or prone to change. Because of the uncertain nature of a priori market attractiveness information and limited experience with new businesses or markets, actual outcomes remain unclear (Hamel and Prahalad 1994; Robinson and Min 2002; Tellis and Golder 1996).[1] Thus, marketing managers need to reevaluate market attractiveness and decide whether to stay in or exit a market (Biyalogorsky, Boulding, and Staelin 2006; Bolton 2003), possibly with a formal model of firm learning (DeGeus 1988).[2] However, firms differ widely in their a priori market attractiveness evaluations and in their learning about true market attractiveness over time, which results in differences in their exit decisions. Insights into firm heterogeneity in terms of market attractiveness evaluations and learning after market entry may enhance the quality of market exit decisions and prevent future business losses or potential bankruptcies (Boulding, Morgan, and Staelin 1997).

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[1] The intrinsic attractiveness of a market includes factors that are important for firm survival, though some may not be obvious and cannot be inferred with certainty before market entry (e.g., hidden costs, competition, consumer mix, consumer response, consumer willingness to patronize, markets' amenability to expansion).

[2] DeGeus (1988, p. 74) stresses the need for a formal model of firm learning: "First, although models in the human minds are complex, most people can deal with only three to four variables at a time and do so through only one or two times iterations.... The second reason for putting mental models into computers is that in working with dynamic models people discover that in complex systems (like markets or companies), cause and effect are separated in time and place. Learning is not a luxury. It is how companies discover their future."

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Our methodological approach posits that at the time of market entry, a firm has an initial belief about a market's attractiveness based on the market's demand. After entry, actual observed demand during each period provides information about true (intrinsic) attractiveness. The firm then updates its belief in a Bayesian manner. Depending on its current beliefs about intrinsic attractiveness, as well as other firm- and market-level factors, the firm decides either to continue for one more period or to exit the market. The firm chooses to exit a market when its current beliefs about intrinsic attractiveness, after market and firm factors are adjusted for, fall below a threshold. If the firm decides to continue, its current intrinsic attractiveness beliefs become the prior belief for the next period. By estimating both initial belief about attractiveness and true attractiveness, this approach helps us determine whether firms use market information to update their prior beliefs about market attractiveness (Biyalogorsky, Boulding, and Staelin 2006).

The Bayesian learning approach follows a rich tradition of learning models in the marketing literature. Roberts and Urban (1988) use this framework to study the adoption of a durable good by a consumer who is uncertain about the attributes of the product but learns about them in a Bayesian manner. Erdem and Keane (1996) also assume Bayesian updating in the context of consumers learning about the quality of packaged goods. In addition, they allow for consumers' expectations of future prices, which results in a dynamic choice problem. More recently, the framework of Bayesian learning has been invoked to understand physician prescription behavior over time (e.g., Narayanan, Manchanda, and Chintagunta 2005). In contrast, with models that attempt to understand how consumers update their beliefs about a product's or brand's true quality, we take the perspective of a firm learning about the attractiveness of a market (e.g., Hitsch 2006).

For the empirical application of our model, we focus on market exits by a specific type of firm, namely, the new entrant discount airline.[3] Recent research has recognized the importance of and the social, competitive, and economic impacts of emerging low-cost formats (i.e., discounters) in various businesses (Gatignon and Anderson 2001; Singh, Blattberg, and Hansen 2005). In the airline industry, passengers have saved more than $6.3 billion annually as a result of low-cost discount airlines (U.S. Department of Transportation 1996). Smaller communities that are not well served by major airlines (and therefore pay more for access) actively try to attract low-cost discount carriers (*USA Today* 2001). Furthermore, recent studies have investigated aggressive competitive reactions by dominant incumbents in certain markets that may lead to market exit by discount airlines and potentially harm consumer welfare (Dixit et al. 2006).

At a broader level, a discount airline entering a new city-pair market is akin to the launch of a new product. Consequently, understanding the reasons for market exit can provide managers with insights into the reasons for the failure of a product, including whether these reasons are more exogenous in nature and associated with the characteristics of the market or whether they are due to factors that firms can control. With an increased understanding of market exit behavior, firms can concentrate on factors that are most critical for their survival (Witteloostuijn 1998), better understand their own decision-making processes, and increase their evaluation efficiency (Sheppard 1994). Our methodology can be adapted to study other exits or failures—for example, new products (Biyalogorsky, Boulding, and Staelin 2006; Hitsch 2006), television shows (Kennedy 2002), or agency–client relationships (Baker, Faulkner, and Fisher 1998).

Our research makes three main contributions. First, we add to the important but underresearched area of market exit by integrating the concept of firm learning with market- and firm-specific factors. Second, we offer a methodological approach that combines a learning model with a binary logit model that considers the impact of various factors on exit behavior and helps forecast market attractiveness in various "what-if" scenarios. Third, we provide an empirical application using data from discount airlines. We find that airlines' prior beliefs about market attractiveness are not necessarily consistent with the market's intrinsic attractiveness and that they learn about the true market attractiveness over time. There is significant heterogeneity in the learning across firms and markets. The results also indicate that a combination of several market and firm factors influences exit behavior. Some factors, such as price, are within the control of the firm, implying that our results can be used as inputs for decision making. Other factors are within the control of the airport and can be used by towns and cities to market themselves to potential entrants.

Firm Learning and Market Exit

The robust stream of research on organizational learning includes academic strategy and marketing researchers who have studied firms' learning processes (for discussions and reviews, see Garvin 1993; Sinkula 1994; Slater and Narver 1995). According to Day (2002, p. 240), "Organizations continuously learn about their markets ... [and] gain an advantage by anticipating market opportunities ahead of their rivals and more accurately forecasting how markets will respond to their moves." Garvin (1993) stresses the need for strategic problem solving, management, and measurement for organizational learning that is based on the firm's own experience and learning from others' mistakes. Slater and Narver (1995) and Sinkula (1994) describe the process of organizational learning through systematic information acquisition to improve performance and gain competitive advantage.

Academic marketing research has also examined the role of managers' prior beliefs and the escalation of commitment in contexts with decision-making uncertainty (Kalyanram, Robinson, and Urban 1995; Robinson and Min 2002; Tellis and Golder 1996). Zajac and Bazerman (1991) point to competitive blind spots, irrational commitment escalations, overconfidence in judgments, and limited perspectives, and they frame the exit problem as being a result of errors in decision making that lead to firm failure or setbacks. Research on the winner's curse further illustrates how firms can suffer judgment errors (Tellis and Golder 1996); other firms may follow "herd behavior" in market entry and exit as well (Kennedy 2002).

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[3] We define a discount airline as one that operates a limited number of routes with costs significantly lower than those of larger, national carriers. This definition precludes Southwest Airlines, which has evolved into a large carrier that operates many routes.

Research in the area of new product introduction suggests that the improper use of initial beliefs, or stickier priors, in the face of negative new information can lead to escalation bias and, ultimately, to the failure of new products (Biyalogorsky, Boulding, and Staelin 2006; Bolton 2003). Biyalogorsky, Boulding, and Staelin (2006, p. 108) find that "the driving force behind the escalation behavior is improper use of initial positive beliefs in the face of negative new information." Whereas this research examines learning as a key behavioral underpinning of failure or exit, research in economics and industrial organization points to other relevant factors.

According to the industrial organization literature, macroeconomic, market-level, and firm-level factors account for exit heterogeneity (Audretsch, Houweling, and Thurik 1997; Ghemawat and Nalebuff 1990). Research on firm-specific factors employs concepts such as firm size, growth rate, age, costs, and so forth (e.g., Asplund and Sandin 1999; Fudenberg and Tirole 1986; Hopenhayan 1992; Klepper and Simmons 2000; Mata, Portugal, and Guimaraes 1995). Within a particular industry, young firms may lack knowledge and experience or may not have sufficient resources to continue their operations (Jovanovic 1982). Audretsch (1991) studies industrial firms and finds that various factors, such as innovation rate, estimated economies of scale, and so on, influence new firm survival rates. Using a Dun & Bradstreet database of new establishments in the manufacturing sector, Audretsch and Mahmood (1995) find that size, innovation rate, and price–cost margin influence exit decisions. Mata, Portugal, and Guimaraes (1995) also posit that size is an important determinant of chances for survival for de novo entrants.

Research on market factors includes demand conditions, the number of firms in the market, growth rate, and concentration (e.g., Agarwal and Gort 1996; Caballero and Hammour 1994; Jovanovic and McDonald 1994; Van Kranenburg, Palm, and Pfann 2000). In a study of automobile tire manufacturers, Jovanovic and McDonald (1994) find that firms that are unable to adjust to a new technological regime exit the market, which implies that a "shakeout" follows a rise in innovation. An increase in the number of firms increases industry size, which in turn is related to higher exit rates (Ilmakunnas and Topi 1999). Agarwal and Gort (1996) study survival rates in various U.S. manufacturing industries on the basis of the developmental stages of the market and product life cycle. They argue that exit is determined by competitive intensity and find that late entrants have relatively lower survival rates.

Asplund and Sandin (1999) argue that high failure rates may be related to uncertain consumer demand for new products. For the Swedish beer market, they find that firms keep winning products in the market and withdraw unsuccessful products. They note (p. 220),

> Even though we do not have a formal theoretical model to use as a framework for our empirical work, we believe that the following story captures the essence of firms' decisions to withdraw products: A firm introduces a new product without knowing the demand for it, as in Raubitscheck (1988). After some time it will become clearer if consumers prefer the new product to existing varieties and what the costs are of keeping it in the market. The future demand for the product can imperfectly be predicted by its past and current market shares.... Over time, the firm will update its beliefs about all these factors and decide on whether the product should be withdrawn or not.

Asplund and Sandin do not formalize this story in their article but estimate a standard hazard function model to study exit durations. In contrast, our proposed model offers an attempt at such formalization.

Overall, research in economics concentrates on market- and firm-related factors, with a preponderance of market factors to explain market exit (Van Kranenburg, Palm, and Pfann 2002). The standard approach to investigating firm exit behavior applies hazard function models to study the influence of (time-varying) covariates on exit behavior. Such an approach offers an assessment of the relative importance of market and firm factors while accounting for any "duration dependence" in the data to reflect the intrinsic probability of exiting the market at different times, after the effects of covariates are controlled for. However, no explanation is available for the estimated pattern of duration dependence, that is, why the intrinsic probability of exiting in period t differs from that in period s. At this junction, the notion of firm learning and the proposed formal belief-updating/learning model, as it is related to firm market exit, can supplement this important research stream. We present selected research on firm learning and market exit in the Appendix.

Empirical Specification

Our dependent variable of interest is whether a discount airline exits from a city-pair market in a particular period, given entry into that market. Our data consist of quarterly information from 1991 to 1999. We observe all entries by discount carriers into various city-pair markets during this period. In each quarter (t), we observe whether an airline (i) exited from the market (m) it entered ("exit") or did not exit ("no exit"), which serves as our dependent measure. Thus, our unit of analysis is the airline–city-pair combination observed for each quarter after entry to the time of exit or the end of the data period, whichever is first. We also observe values of demand and the various covariates in each period, including firm-specific factors, market structure characteristics, and economic factors associated with the market (i.e., city pair). The model assumes that the airlines also observe this information.

A firm begins with an initial prior belief about the intrinsic attractiveness of the market it has entered. Because of the uncertainty regarding the market's attractiveness, we represent this initial prior belief as a distribution. How does a firm resolve its uncertainty regarding market attractiveness? Essentially, it uses the new information it obtains from that market in each quarter to update its beliefs about market attractiveness. The amount of new information available to the firm in each quarter is the realized per capita market demand across all airlines in the previous quarter.[4] Belief updating takes places in a Bayesian manner; the firm combines its prior belief with the new information to arrive at a posterior (or updated) belief of that market's attractiveness.[5] The firm then uses this set of posterior beliefs to make a decision to stay in or exit the market for the quarter, and the set of posterior beliefs forms the prior beliefs for the next period.

Note that we use per capita market demand rather than demand per se as the amount of new information. A consequence of using aggregate market demand directly is that airlines will obtain more information from larger markets than they will from smaller markets purely as a consequence of market size (because larger market sizes usually imply more demand for air travel). Because the speed of learning in a model of Bayesian updating such as ours depends on the amount of new information available in each period, it would imply faster learning in larger markets. In reality, however, there could be considerable heterogeneity in the speed at which firms learn about market attractiveness; that is, they could learn as fast in certain small markets as they would in certain large markets. To allow for this possibility and exploit the information contained in realized market demand, we use demand adjusted by the populations of the origin and destination cities (per capita demand) to represent the amount of new information that firms use to update their beliefs about market attractiveness.[6] We assume that airlines receive the information on demand from the previous quarter at the beginning of the next quarter and that this information becomes the amount of information nd_{mt} for city-pair market m in quarter t available to the firm for belief updating.

Stay or Exit Decision

In each period or quarter, the firm compares the overall attractiveness of staying in the market with some threshold attractiveness level. If the expected attractiveness exceeds the threshold level, the firm stays in the market; otherwise, it exits the market. The overall attractiveness of a market pertains to the expected economic profit and other strategic factors, such as the market's importance to the firm, the influences on overall costs, and so forth.

Let π_{imt} denote the expected overall attractiveness to airline i (i = 1, 2, ..., I) of staying in market m (m = 1, 2, ..., M) in quarter t (t = 1, 2, ..., T_{im}, or the number of quarters the airline stays in market m), and let $\bar{\pi}_{im}$ denote the threshold level below which the firm exits (which could include the cost of exit). A firm decides to stay if $\pi_{imt} \geq \bar{\pi}_{im}$ and exits if the inequality is reversed. The overall attractiveness measure does not account merely for profits; rather, expected overall attractiveness of market m to firm i in quarter t is a function of the intrinsic attractiveness of the market, the prices charged by the firm and its rivals, cost drivers, firm and environmental characteristics, and other factors observed by the firm but not by the researchers. As we noted, this metric reflects the level of firm profits in that market. Given the complexity of airline markets and the variation in market structures, as well as the nature of competition across markets, we do not provide a structural characterization of this function for each firm for each market it enters. Instead, we follow recent literature in economics (e.g., Seim 2004) and specify the function in reduced form. Specifically, we approximate π_{imt} as

$$\pi_{imt} = E(\tilde{A}_{imt} + X_{imt}\beta_m + Z_{im}\gamma_m + \varepsilon_{imt}), \tag{1}$$

where E(·) is the expectation operator and $\tilde{A}_{imt}$ denotes firm i's belief about the intrinsic attractiveness of city-pair market m in quarter t. The symbol ~ indicates that attractiveness is a random variable from the firm's point of view. Let $\bar{A}_{imt}$ denote the mean of $\tilde{A}_{imt}$ at time t, and let the variance of the belief be σ^2_{imt}. The term X_{imt} contains all the time-varying drivers of market attractiveness; Z_{im} contains the time-invariant drivers; β_m and γ_m denote the effects of the former and latter sets of drivers on attractiveness, respectively; and ε_{imt} represents the unobserved (to researchers) factors that drive attractiveness. Thus, $\tilde{A}_{imt}$ is a random variable and the only term on the right-hand side of Equation 1 that is not directly observed by the firm. We obtain expected overall attractiveness as follows:

$$\pi_{imt} = \bar{A}_{imt} + X_{imt}\beta_m + Z_{im}\gamma_m + \varepsilon_{imt}. \tag{2}$$

The observed outcomes in the market are whether an airline chooses to stay (1) or exit (0) in a given quarter. Because we do not observe ε_{imt}, we must assume that it follows some distribution. If we assume that the error term ε_{imt} in Equation 2 is distributed as extreme value Type I, the probability that the firm stays in the market can be written as

$$P_{imt} = \frac{\exp(\bar{A}_{imt} - \bar{\pi}_{im} + X_{imt}\beta_m + Z_{im}\gamma_m)}{1 + \exp(\bar{A}_{imt} - \bar{\pi}_{im} + X_{imt}\beta_m + Z_{im}\gamma_m)}, \tag{3}$$

where the probability of exit = 1 – P_{imt}.

Learning About Intrinsic Attractiveness

Thus far, we have introduced two terms that are central to firms' learning behavior: $\tilde{A}_{imt}$, which denotes firm i's belief about the intrinsic attractiveness of city-pair market m in quarter t, and nd_{mt}, which denotes the amount of information firms in market m and quarter t use to update their beliefs about $\tilde{A}_{imt}$. Next, we relate the two terms in the context of the Bayesian learning process (see also Erdem and Keane 1996). Let A_{im} denote the intrinsic attractiveness of market m for firm i. If firms observed this measure, there would be no uncertainty and, thus, no learning. In reality, firms do not observe A_{im} but have some beliefs about its value.

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[4] An issue is whether airlines have ready access to this information. The Bureau of Transportation statistics provides timely information (see http://transtats.bts.gov). Furthermore, we assess the sensitivity of our results to information from prior periods when the immediately preceding quarter's data are unavailable.

[5] In principle, we can extend this analysis to include other sources of information.

[6] In reality, an airport serves a population larger than just the populations of the origin and destination cities. We recognize this as a potential limitation of our measure, but we use it in the absence of an alternative metric.

At time t = 0, we assume that the airline's initial belief about the intrinsic attractiveness of the market is normally distributed:

$$\tilde{A}_{im0} \sim N(A_{im0}, \sigma^2_{im0}). \tag{4}$$

We assume that the mean of the initial belief A_{im0} is a function of market size (i.e., the total number of travelers in that market pair) in the period before entry. Specifically,

$$A_{imo} = \lambda_{i0} + \theta S_{m0} + \nu_m, \tag{5}$$

where λ_{i0} is a firm-specific parameter, S_{m0} is the size of market m before firm i's entry (we mean-center S_{m0} in the estimation to interpret λ_{i0} directly as the mean of the initial belief across markets), θ is an unknown parameter, and ν_m is a market-specific factor that influences the mean initial belief.

At the beginning of Quarter 1 (after entry), the firm has not yet received any information from the market (note our assumption that all information is received at the beginning of the quarter). Thus, its posterior belief about market attractiveness at t = 1 is still the prior from Equation 4.

At the beginning of Quarter 2, the firm has a prior belief that reflects the posterior belief about market attractiveness at t = 1. The firm now receives information contained in the per capita market demand during Quarter 1, nd_{m2}. This information provides noisy but unbiased signals regarding A_{im} to the firm. The firm then uses these signals to update its belief from Quarter 1 and obtains a Quarter 2 posterior distribution for $\tilde{A}_{im2}$. In particular, we assume that the firm receives nd_{m2} unbiased signals, with each signal being a draw from the distribution $N(A_{im}, \sigma^2_m)$. Thus, each signal, j = 1, 2, …, nd_{m2}, can be written as follows (where we replace the time subscript 2 with the general subscript t):

$$D_{imtj} = A_{im} + \omega_{imtj}, \quad \omega_{imtj} \sim N(0, \sigma^2_m). \tag{6}$$

The firm now combines the prior belief with this information to obtain its posterior beliefs for Quarter 2. Given that the initial prior distribution and information are normally distributed, the resultant self-conjugacy implies that the posterior belief should be normally distributed. Thus,

$$\tilde{A}_{im2} \sim N(\bar{A}_{im2}, \sigma^2_{im2}), \tag{7}$$

where $\bar{A}_{im2}$ is the mean of the distribution and σ^2_{im2} is the variance of the posterior belief. This $\bar{A}_{im2}$ enters Equation 3 as the probability of the airline staying in the market in Quarter 2. This process repeats for all future quarters with the posterior for Quarter 2 becoming the prior for Quarter 3, and so on.

For any period t, the mean of the posterior belief $\bar{A}_{imt}$ can be written as in the following recursive equation:

$$\bar{A}_{imt} = \theta_{imt}\bar{A}_{im(t-1)} + \varphi_{imt}\bar{D}_{imt}, \tag{8}$$

where $\bar{A}_{im(t-1)}$ is the mean of the posterior belief from period (t − 1) and $\bar{D}_{imt}$ is the mean value of the information content of all information received in period t. The various terms in this equation are defined as follows (these are standard formulas for normal prior–normal information distributions; see DeGroot 1986; Erdem and Keane 1996; Narayanan, Manchanda, and Chintagunta 2005):

1. The weight given to the previous period's posterior mean is

$$\theta_{imt} = \frac{1}{\sigma^2_{im(t-1)}}/L.$$

2. The weight given to current period information is

$$\varphi_{imt} = \frac{nd_{imt}}{\sigma^2_m}/L.$$

3. In Points 1 and 2, the denominator is defined as

$$L = \frac{1}{\sigma^2_{im(t-1)}} + \frac{nd_{jt}}{\sigma^2_m}.$$

4. The mean value of the information content received in t is

$$\bar{D}_{imt} = \sum_{j=1}^{nd_{imt}} \frac{D_{imtj}}{nd_{imt}} \sim N\left(A_{im}, \frac{\sigma^2_m}{nd_{imt}}\right).$$

5. The variance of the period t posterior distribution is

$$\sigma^2_{imt} = \frac{1}{L} = \frac{1}{\frac{1}{\sigma^2_{im0}} + \sum_{\tau=1}^{t} \frac{nd_{im\tau}}{\sigma^2_m}}.$$

In the estimation, we must normalize the variance of the initial attractiveness σ^2_{im0} to 1 for identification purposes. Because expected overall attractiveness is a function of intrinsic attractiveness, which already embeds an intercept term in intrinsic attractiveness A_{im}, we cannot separately identify $\bar{\pi}_{im}$. Therefore, for estimation purposes, we normalize $\bar{\pi}_{im}$ to 0.

The likelihood function for airline i in city-pair m that decides to exit the market t_{im} quarters after it enters is given as follows:

$$\ell_{im} = \left(\prod_{k=1}^{(t-1)_{im}} P_{imt}\right)(1 - P_{imt}). \tag{9}$$

If the airline does not exit by the end of the data collection period, the likelihood will be

$$\ell_{im} = \left(\prod_{k=1}^{t_{im}} P_{imt}\right). \tag{10}$$

Discussion of the Model

It is important to understand the distinction between the per capita demand nd_{mt} and the demand signals D_{imtj}, j = 1, 2, …, nd_{mt}. The former simply represents the observed demand in the marketplace (per capita) and therefore is known to both the firm and the researchers. However, D_{imtj}, j = 1, 2, …, nd_{mt}, correspond to nd_{mt} and represent the information the firm extracts from the demand, which it then uses to make inferences about market attractiveness, including, for example, the proportion of business versus leisure travelers, regular versus one-time travelers, travelers flying for a specific conference, and so forth. This information is known to the firm but not to the researchers. We discuss how we deal with these unobserved signals in the "Estimation" subsection. A plausible alternative formulation might assume that nd_{mt} is a direct signal that firms use, in which case both the firms and the researchers would observe them. In this case, $nd_{mt} \sim N(\alpha_0 + \alpha_1 A_{im}, \sigma_m^2)$, where the parameters α_0 and α_1 equalize the units of measurement of nd_{mt} and A_{im} and must be estimated. With our data, however, we find that this model does not fit as well as the proposed model.

Heterogeneity

We use a random coefficient approach to account for heterogeneity (e.g., Allenby and Rossi 1999). The set of parameters that varies across markets m and firms i in the preceding discussion is $\{A_{im}\}$, and the set of parameters that varies across markets is $\{v_m, \beta_m, \gamma_m, \sigma_m^2\}$. With respect to the intrinsic market attractiveness parameters, a simple approach would estimate an airline–market intercept for each airline operating in each city-pair market. Such a "fixed-effects" approach is feasible only for markets for which a long time series of observations is available. Instead, we use a random-effects approach and assume that A_{im} is a draw from a parametric distribution. One option would be to assume that A_{im} for each airline i is a draw from the univariate distribution—for example, a normal distribution such as $A_{im} \sim N(A_i, \sigma_i^2)$. In this case, σ_i^2 captures the variation across markets m of airline i's intrinsic market attractiveness. Such a random-effects specification implies estimating as many mean and variance parameters as there are airlines in our data. However, this specification ignores correlations across airlines. For example, for all airlines based in the southeastern United States, markets on the West Coast may be less attractive than those on the East Coast. To account for such correlations, we assume that the intrinsic attractiveness parameters are draws from a multivariate normal distribution, as follows:

$$A_m \sim MVN(A, \Omega). \tag{11}$$

In Equation 11, A_m denotes a vector of dimension I, or the number of airlines. In our case, because our data include eight airlines, Ω is an 8 × 8 matrix with 36 unknown parameters. (Note that if the off-diagonal elements are zero, this matrix reduces to the univariate specification.) To reduce the computational burden of estimating 36 covariance parameters, we impose a two-factor structure on the covariance matrix Ω (e.g., Erdem 1996). Thus,

$$\Omega = (Z\delta)(Z\delta)', \tag{12}$$

where Z denotes an 8 × 2 (airlines × factors) matrix of location parameters and δ denotes a 2 × 1 random vector of importance weights with a bivariate normal distribution with a mean of 0 and a two-dimensional identity matrix for the covariance matrix. One of the elements of the Z matrix is normalized to 0 to account for rotational invariance, and δ accounts for scale invariance. Thus, our model structure allows intrinsic attractiveness to be correlated across airlines parsimoniously. We capture heterogeneity in the remaining parameters as follows:

$$\{v_m, \beta_m, \gamma_m, \ln(\sigma_m^2)\} \sim MVN(\{v, \beta, \gamma, \sigma\}, \Sigma). \tag{13}$$

In the estimation, we constrain Σ to be a diagonal matrix. Recall that v_m is a market-specific factor that influences the mean initial belief; β_m and γ_m denote the effects of time-varying and time-invariant drivers of attractiveness, respectively; and σ_m^2 denotes the variance of the demand signal. Our assumption effectively implies that these factors are uncorrelated. In general, a correlated structure might be preferred; however, such an approach substantially increases the computational burden involved, which would require us to constrain either Ω or Σ as a diagonal matrix. Allowing for the latter produces a better model fit.

Estimation

The sample likelihood function can be written as

$$\ell = \prod_{i, m} \int \ell_{m} dF(A_{im}) dF(\{v_m, \beta_m, \gamma_m, \ln(\sigma_m^2)\}). \tag{14}$$

The product in Equation 14 is taken across all airline and city-pair market combinations observed in the data. We use simulated maximum likelihood for the estimation, which is standard except for one complication, namely, the presence of the demand signals D_{imtj} in Equation 6. These demand signals are observed by the firms in the market but not by the researchers. What we observe instead is the amount of information the firm receives, nd_{mt}, in each market m and each period t. We also know that the demand signals D_{imtj} are independent and identical draws from a normal distribution with mean A_{im} and variance σ_m^2. In the estimation, therefore, we simulate these signals, conditional on the parameters A_{im} and σ_m^2, and use them to compute the mean of the posterior distribution in Equation 8. Such an approach has been used in previous research (e.g., Narayanan, Manchanda, and Chintagunta 2005). After we construct this posterior mean $\bar{A}_{imt}$, we return to the structure of a standard random coefficients logit model.

Applicability

A firm's prior belief about a market's attractiveness is influenced by the size of the market before the firm enters it (Equation 5). In addition, the firm has information about several firm and market factors before its entry. The key pieces of missing information are own and competitor prices and actual demand after entry (which represents the basis of the belief update). A new entrant can perform a what-if analysis by varying the levels of these factors and identifying the associated level of market attractiveness. A related option is to identify similar markets and then use the levels of prices and demand from those markets to predict attractiveness. For an airline already in the market, making a prediction about attractiveness for the next quarter is straightforward because the firm observes both nd_{mt} and D_{imtj}, j = 1, 2, …, nd_{mt}. For periods beyond the next, the firm must use what-if analyses with simulated levels of demand and associated signals.

Data and Variables

We obtained data for the U.S. airline industry from the Origin and Destination Syndicated Survey of Air Passenger Traffic. The Origin and Destination database consists of a 10% random sample of all airline passenger tickets issued by all airlines on a quarterly basis. We focus on the period from Quarter 1/1991 to Quarter 4/1999, the 110 largest cities in the United States, and 25 major and discount airlines that accounted for more than 80% of the total population of passengers flying. Data are available for each city pair or market. For cities with multiple airports, the data are at the airport-pair level. Because we need data from the time of entry, we limit our attention to market entry after Quarter 1 1991, so either the airline exits before Quarter 4 1999 or the data are right censored. Note that a particular airline can enter the market, maintain its market presence for a few quarters, exit, and then reenter in a subsequent quarter. We code an airline as having exited from a market if it did not operate in the market for two consecutive quarters.

An important issue for our data is the influence of discount airlines (e.g., Southwest) that existed before 1991. Some of these airlines might exit from the market in the 1991–1999 period, whereas others might continue to operate until the end of the time window. As we describe subsequently, our specification includes a variable that represents the number of discount airlines in the market in each period, which changes if preexisting carriers exit the market. Thus, we control for the exit behavior of other airlines when we study the behavior of our focal airlines.

Variables

For the key variable for learning in our analysis, the information received in any quarter t, nd_{mt}, equals the (population-adjusted) demand across all airlines in the previous quarter. Its variation over time accounts for any possible growth or decline in the market. Although critical for our analysis, this variable enters the model formulation as we described previously (Equation 8) but not as part of the matrix X_{imt}.[7] The variables that drive overall market attractiveness or, more generally, the factors that influence the stay versus exit decision include two sets of variables that influence exit: market features and firm-specific characteristics. Table 1 shows the means and standard deviations of continuous covariates across 5084 observations in the data. For the discrete variables, we report the proportion of times the variables took the value of 1. Of the eight major discount carriers in the data, AirTran, Frontier, ValuJet, and ATA account for a majority of the observations, and the remaining four each have a share of observations of less than 10%, with Midwest Express at approximately 10%. The data contain 497 exits, with an average duration in the market of five quarters. The remaining 392 entries do not result in an exit. Fewer than 10% of the airlines that exited the market reentered.

TABLE 1
Descriptive Statistics of Covariates

Variable	M	SD
Market Factors		
Population × 10^{-4} (POP)	.055	.051
Per capita income × 10^{-5} (PCI)	.313	.037
Distance × 10^{-4} (DS)	.110	.056
Vacation city (VC)	.344	
Gate controlled (GC)	.059	
Slot controlled (SC)	.070	
Season 1 (Q1)	.201	
Season 2 (Q2)	.257	
Season 3 (Q3)	.263	
Diffusion–Year 1	.542	
Diffusion–Year 2	.266	
Preentry market size × 10^{-5} (S_{m0})	.039	.051
Firm Factors		
Own price × 10^{-2} (P)	1.401	.645
Competitor price × 10^{-2} (CP)	1.541	.504
Cost per seat mile (CPSM)	.093	.019
Number of major competitors (NMC)	5.928	1.587
Number of discount competitors (NDC)	1.534	1.065
Origin city hub (OCH)	.083	
Destination city hub (DCH)	.076	
Number of rivals with hubs (NRH)	.952	1.106
Carrier size ×10^{-5} (CS)	.057	.032
Airline Dummies		
Frontier	.164	
AirTran	.244	
ValuJet	.123	
Vanguard	.065	
Spirit	.025	
Reno	.081	
ATA	.185	
Midwest Express	.112	

Market Factors

In line with Berry (1992) and Dresner, Lin, and Windle (1996), who use the product of the populations of two cities, we use the geometric mean of the populations of the origin and destination cities to measure the population for that city-pair market. Although population can vary over time in principle, these variations are not significant for our periods. We denote population for market m as POP_m. The bigger the population, the greater is the attractiveness of a market. However, firms also might compete more fiercely for such markets, which may raise the probability of exit.

We follow Dresner, Lin, and Windle (1996) and, similar to our population variable, denote per capita income for market m as PC_m. All else being equal, we expect that overall attractiveness is higher in markets with higher per capita incomes.

We operationalize our distance variable as the distance in air miles between the cities that constitute the market pair (Berry 1992; Dresner, Lin, and Windle 1996). We denote the variable DS_m for city-pair m.

If either of the two cities in the market pair is a vacation destination (with more vacation than business travelers), we code that city pair with a dummy variable VC_m that takes the value of 1 (see Dresner, Lin, and Windle 1996). Discount airlines are more likely to stay in a vacation city market because vacation travelers might be more price sensitive, which would make discount airlines more attractive.

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[7] In the comparison models (i.e., logit and hazard), we include the previous quarter's market size as a variable in X_{imt}.

Gate-controlled markets are those in which airport positions necessary for enplaning and deplaning passengers are controlled by long-term leases held by incumbent airlines. A new airline entering a gate-controlled airport must sublease the gates from the incumbent airlines, which can be difficult and expensive. Including this variable is consistent with Karakaya's (2000) study. We operationalize gate control in market m as a dummy variable that takes the value of 1 if either the origin or the destination city is gate controlled, and we denote it as GC_m.

Similar to gate-controlled airports, slot-controlled airports are governed by federal rules that set hourly quotas of take-offs and landings at the country's busiest airports. Again, incumbents have an advantage because they own long-term leases on the slots at these airports. We operationalize slot control in market m as a dummy variable SC_m that takes the value of 1 if either the origin or the destination city is slot controlled (Dresner, Lin, and Windle 1996).

Although not strictly a market factor, we consider seasonal factors because markets may be more or less attractive during specific seasons. Airlines likely announce exits from markets in particular quarters depending on a variety of factors, such as when financial statements need to be filed, typical lead times for consumers to make reservations for vacation destinations, and so forth. We include three seasonal dummies to reflect the January–March (Q1), April–June (Q2), and July–September (Q3) quarters. Thus, the base quarter is October–December (Q4). These variables, which we denote as $Q1_t$, $Q2_t$, and $Q3_t$, take the value of 1 if quarter t corresponds to Q1, Q2, or Q3.

In the periods immediately following entry, the penetration of an airline in a market could be lower as a result of diffusion effects within the population that constitutes the local market. To account for this possibility, we introduce dummy variables for each of the first two years the airline exists in a market.

The attractiveness of a market is related to the number of travelers at the time of entry. In our analysis, we allow the preentry size of the air travel market (S_{m0}) to influence a discount airline's prior belief about the attractiveness of the market (Equation 5). As we noted, we mean-center this variable for easy interpretation of the λ_{i0} parameter.

Firm-Specific Factors

The own-price variable represents the average one-way price P_{imt} that discount carrier i charges for city-pair market m in quarter t. It equals the ratio of the total revenues for the route to the total number of passengers. Because data are not available by fare class, we construct this measure with some caution, but it provides a means of controlling for within-market time-series variation in price.

We compute the competitor price variable as the share-weighted average across all rivals of the discount airline. A higher price charged by rivals should make the market more attractive to discount airlines. We denote this variable for discount airline i, market m, and quarter t (CP_{imt}).

Costs are significant when firms decide to stay in or exit a particular market. Although our data do not include market-specific cost information for each airline, we have quarterly data about each airline's cost per seat mile ($CPSM_{it}$).

Including the number of major competitors in a market is consistent with research by Van Kranenburg, Palm, and Pfann (2002). We divide the competitors the discount airline faces in a given market m into two groups. The first group consists of competitors that are typically characterized as "major" or "national" airlines, such as United, American, Delta, Continental, Northwest, and US Airways. The second group consists of other discount carriers that may be operating in city-pair m. Although these variables typically do not vary over the duration of the new entrant's operations in the market, they could vary over time, so we denote them as NMC_{imt}. Our definition of the number of discount competitors follows from the description of our previous variable. We denote this variable as NDC_{imt} and again expect that greater numbers of discount carriers lower market attractiveness. Subsequently, we address the endogeneity concerns created by including these two variables.

We create origin city hub as a dummy variable that takes the value of 1 if the base city in the pair is a hub for the discount carrier and 0 if otherwise. This market- and carrier-specific variable is time invariant, and we denote it as OCH_{im}. Because the label "origin" or "destination" city is arbitrary for any given city pair, we also account for whether the destination city is a hub. Again, we use a dummy variable and denote it as DCH_{im}. We expect that the effect of this variable on exit is the same as that of OCH_{im}. For the major airlines, the likelihood of either the origin or the destination city being a hub is high; however, the same is not true for discount airlines.

The rivals of the discount carriers that have hubs in the markets under consideration are likely to compete more fiercely than others. Therefore, we include a variable that reflects the number of airlines that use either the origin or the destination city as a hub. We denote this measure of carrier i (number of rivals of carrier i) and market m as NRH_{im}.

Following Mata, Portugal, and Guimaraes (1995), we include a carrier size variable. As a discount carrier becomes larger, operates in more markets, and carries more passengers, its likelihood of surviving in markets in which it operates increases. Carrier size also acts as a proxy for the financial strength of the airline. Therefore, we include the variable CS_{it} to reflect the total number of passengers carried by the discount carrier across all markets in quarter t. We use a time-varying measure, in line with recommendations in previous research (Mata, Portugal, and Guimaraes 1995). We also test the lagged value of this variable, but it does not affect the results.[8]

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[8] The correlations between some key variables are as follows: own price and competitor price = .318, own price and cost per seat mile = .233, and own price and carrier size = –.024. The range of correlations between own price and other variables is [–.175, .380]. The highest correlation (in absolute value) across all variables is .681 between population and slot control.

In addition to these variables, we note several firm-specific factors that are constant across markets, such as firm reputation (Stavins 1995), firm age, fleet age at the start of the data period, and fleet size. To capture the effects of these variables, we could include carrier dummies or fixed effects in the specification. In our case, the mean across markets of the intrinsic attractiveness of market m for firm i, or the mean of A_{im} across markets m (Equation 2), takes the role of airline fixed effects.

Empirical Issues

Before describing the data, we address two critical decisions we made about (1) whether to include Southwest Airlines in the set of discount carriers and (2) how to deal with the merger between ValuJet and AirTran. First, although Southwest was a dominant force in the discount carrier movement in the U.S. market, during our data period, it increasingly began to resemble a major national carrier. Furthermore, it seldom exited markets it entered. If we include this airline, the total number of market entries for the data collection period is 1428, with 563 exits from various markets. If we exclude it, the total number of market entries drops to 1010, but the total number of exits drops only to 533. In effect, Southwest offers 418 market entries with only 30 exits; this reflects a rate of less than 10%, whereas the rate for all other discount airlines is greater than 50%. In other words, Southwest behaves differently from the other discount carriers in terms of its survival.

We analyze the data both with and without Southwest and find that the substantive results for the effects of covariates are similar across the two models; therefore, we present the results without Southwest. (The results that include Southwest are available on request.) We also dropped EastWind airlines from the analysis because it accounts for a very small share of all observations (.8%) and causes issues with the estimation of heterogeneity in the data.

Thus, the total number of airline–market–quarter observations in the data is 5084; the observation for each quarter represents whether the airline exits the market (value = 0) or not (value = 1). Of our total observations, 497 take the value of 0 (exit), and 4587 (accounting for 392 entries) take the value of 1 (no exit).

The second issue pertains to the merger between ValuJet and AirTran. When the merged airline completely exited a city-pair market, we coded it as an exit. In addition, several of ValuJet's exits and AirTran's entries were not really exits or entries, because AirTran was simply carrying on ValuJet's operations in those markets. Recall that our definition of exit is based on the absence of operations in two consecutive quarters; accordingly, if the time between a ValuJet exit and an AirTran entry in the same city-pair market exceeded two quarters, we coded it as an exit and entry, respectively. However, if we observed an AirTran entry during the two-quarter interval, we did not code a ValuJet exit but rather treated it as continuing operation and measured duration from the time of the initial ValuJet entry. However, because the airline is no longer ValuJet but flies under the AirTran flag, we switched the intrinsic airline attractiveness parameter from a ValuJet dummy to AirTran at the time the latter took over the operations. Thus, we can capture any differences between ValuJet and AirTran in their intrinsic exit probabilities, as reflected in these parameters.[9]

Empirical Results

We use the first 4009 observations for our estimation and the remaining observations for our out-of-sample predictions. The estimation sample includes 398 exits, leaving 99 for the validation sample. In Table 2, we present the first set of empirical results from the model and highlight several noteworthy points. First, intrinsic market attractiveness (A_{im}) seems to vary across airlines. On average, intrinsic market attractiveness is lowest for Reno and ValuJet and highest for ATA and Frontier, followed by Midwest. Second, considerable heterogeneity appears across markets in terms of attractiveness to the airline. In particular, heterogeneity is significant for Vanguard, Spirit, and ATA. We obtain these standard deviation estimates from the two-factor heterogeneity structure discussed in the "Empirical Specification" section. (Rather than report the factors themselves, we provide the implied standard deviations of the heterogeneity distribution, or the square roots of the diagonal elements in the Ω matrix, in Equations 11 and 12.) Third, heterogeneity exists across markets in terms of initial mean attractiveness levels (standard deviation of distribution of ν_m = .499, standard error = .160). Fourth, preentry market size is statistically significant in influencing initial mean attractiveness (θ parameter in Equation 5). Fifth, the variance of demand information (mean value of σ^2_m across markets) is small compared with the variance of initial intrinsic attractiveness (σ^2_{im0}, normalized to 1), which signifies the (relatively) informative nature of demand information. Moreover, significant heterogeneity exists in the variance across markets (estimated standard deviation of σ^2_m across markets = 7.043, standard error = .449). In relative terms, demand information in one market can be significantly more or less informative than that in another market. Another important takeaway is that we find significant learning regarding the intrinsic attractiveness of markets (i.e., λ_{i0} is different from A_{im}; note that S_{m0} is mean centered). This finding contradicts that of Biyalogorsky, Boulding, and Staelin (2006). We argue that the nature of competition in the airline industry and the experience of the players in various markets contribute to greater learning.

To illustrate learning further, we take the case of ATA as an example. The average across-markets estimate of mean initial attractiveness (mean value of A_{im0} across markets) is 8.397 (standard error = 1.323), whereas intrinsic market attractiveness (A_{im}) is 14.971 (standard error = 1.969). The information ATA receives indicates that markets are more attractive than it initially perceived, after we control for the other factors in the market. In contrast, the corresponding estimates for ValuJet are 5.657 and 4.511; that is, ValuJet's

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[9] Reno Air merged in 1999 with American Airlines, though the effects of this merger are not reflected in our data because our period of analysis ends in 1999.

TABLE 2
Parameter Estimates and Standard Errors (Distribution of Intrinsic and Initial Market Attractiveness: A_{im} and A_{im0}, Demand Information Variance: σ_m^2)

Variable	Mean of Distribution M	Mean of Distribution SE	Standard Deviation of Distribution M	Standard Deviation of Distribution SE
Intrinsic Market Attractiveness, A_{im}				
Frontier	12.576	1.377	3.783	.874
AirTran	7.341	1.129	.581	.533
ValuJet	4.511	1.170	.212	.341
Vanguard	8.625	1.211	6.006	1.206
Spirit	7.546	1.525	8.132	1.243
Reno	4.919	1.195	1.891	.509
ATA	14.971	1.969	10.472	2.211
Midwest Express	11.196	1.479	2.182	.703
Factors Influencing Mean Initial Belief of Intrinsic Market Attractiveness: $A_{im0} = \lambda_{i0} + \theta S_{m0} + v_m$ (S_{m0} Is Mean Centered)				
Initial Intrinsic Market Attractiveness, λ_{i0}				
Frontier	5.233	1.154		
AirTran	4.978	1.184		
ValuJet	5.657	1.198		
Vanguard	7.505	1.207		
Spirit	5.528	1.164		
Reno	4.756	1.236		
ATA	8.397	1.323		
Midwest Express	5.958	1.301		
Effect of preentry market size (θ)	3.265	1.021		
Market-Specific Factor Influencing the Mean Initial Belief, v_m	0[b]		.499[a]	.160
Demand Information Variance, $\ln(\sigma_m^2)$	–9.725	.531	7.043	.449

[a] Constrained to be equal across airlines.
[b] Constrained to 0 by presence of initial intrinsic market attractiveness, λ_{i0}.

information indicates that markets are less attractive than it initially perceived.

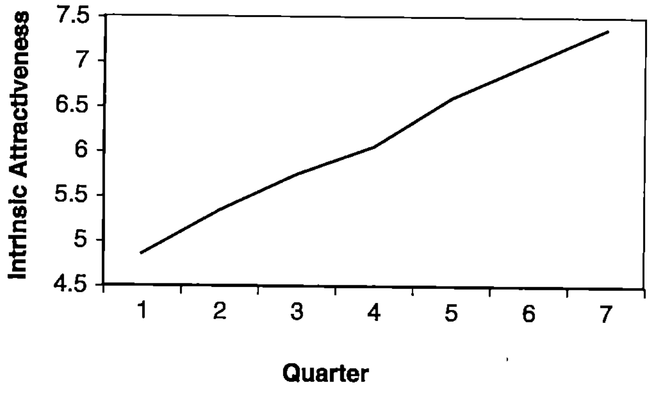
To demonstrate the temporal evolution of intrinsic market attractiveness, we plot some specific and distinct examples of airline markets in Figure 1. We show the evolution of an AirTran (Figure 1, Panel A), ValuJet (Figure 1, Panel B), and ATA (Figure 1, Panel C) market. The AirTran example shows gradual and relatively slow learning during the seven quarters of available data, but this pattern is specific only to this AirTran market, in line with both heterogeneity of intrinsic attractiveness and variance across markets. In the ValuJet example, less learning occurs over time, as is evidenced by the range on the y-axis, which extends only from 5.2 to 5.7. Within this range, we observe a gradual learning rate. Finally, in the ATA case, learning is slow in the first four quarters and then increases at a more rapid pace. We control for diffusion effects in the model, but these learning effects still emerge.

Another way to view the results from the learning model is to track the variance of posterior beliefs about market attractiveness over time (σ_{imt}^2), as we plot in Figure 2 for the same three airlines in different markets. In contrast to Panel A in Figure 1, Figure 2, Panel A, shows that the decline in variance is rapid for the first three quarters and then slows down. For ValuJet (Figure 2, Panel B), we observe a steady decline, whereas for ATA (Figure 2, Panel C), rapid learning occurs initially, in contrast to Figure 1, Panel C.

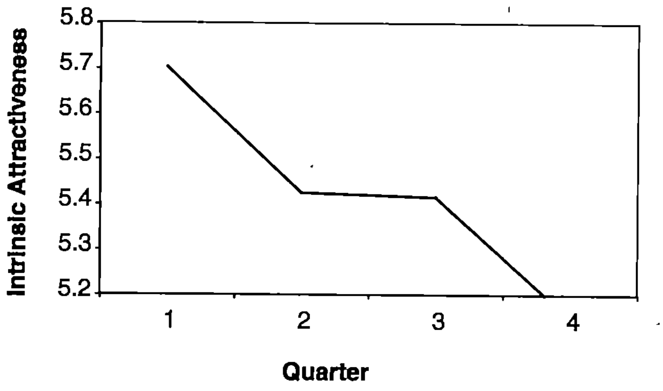
Next, we consider the effects of various market and firm factors on the overall attractiveness of the market (β_m and γ_m) and, thus, on the probability of exit; we present these results in Table 3. Note that we do not allow all these effects to vary across markets according to our previously described random-effects specification. Instead, we allow for heterogeneity only in the coefficient of the own-price parameter. This choice is motivated largely by the computational burden in estimating these parameters and the identification of all the corresponding variance parameters. After controlling for intrinsic market attractiveness, we find three market factors that influence overall market attractiveness. First, the population of the origin and destination cities matters; the larger the population, the more attractive is the market. Second, a lower per capita income of the markets in the city pair increases the attractiveness of the market to the discount airline, consistent with its appeal to more price-sensitive consumers. Third, markets that are gate controlled are less attractive because of the expense and difficulty of subleasing gates from incumbent airlines. Consistent with

FIGURE 1
Intrinsic Attractiveness over Time in Specific Markets

A: AirTran



B: ValuJet



C: ATA

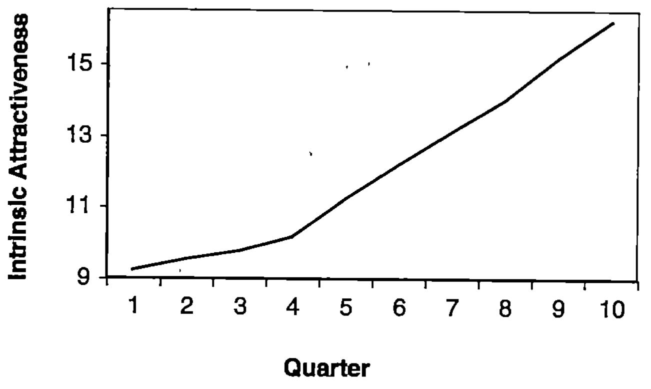
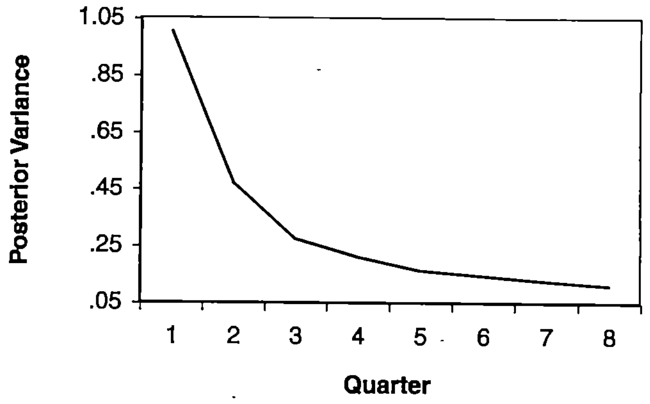
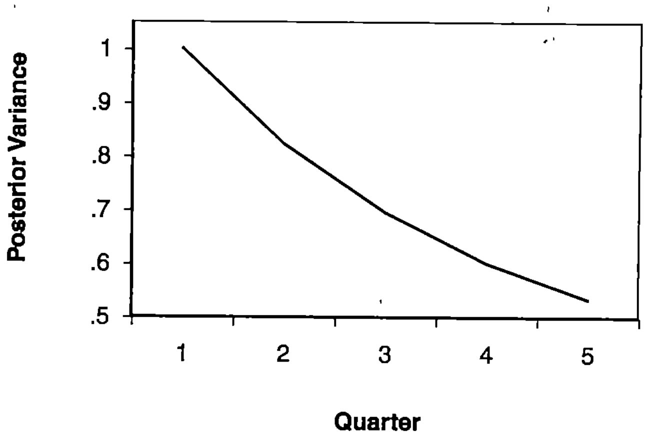


FIGURE 2
Posterior Belief Variance over Time in Specific Markets

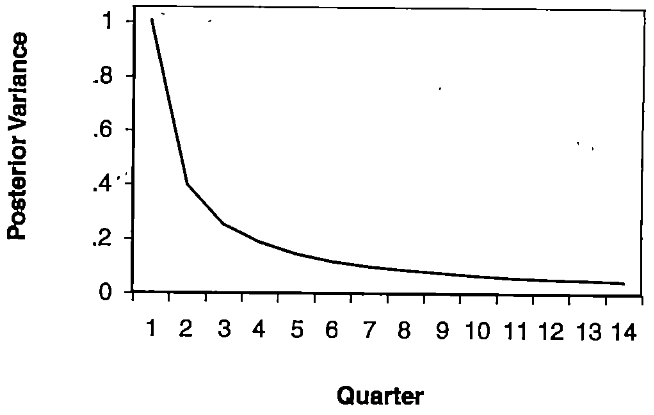
A: AirTran



B: ValuJet



C: ATA



this notion, our estimated effect is negative (–1.175) and statistically significant at the 5% level (standard error = .357).

We also find strong seasonality effects, such that the probability of exit varies by season. Our results further indicate that after we control for all other factors, the attractiveness of a market is highest in the first year after entry (Year 1 dummy variable coefficient = 2.437, standard error = .460), lower in the second year (1.175, standard error = .396), and lowest thereafter (base value = 0). This finding runs somewhat counter to our expectations based on a standard diffusion argument. However, the year dummy may act

TABLE 3
Parameter Estimates and Standard Errors (Effects of X_{imt} on Probability of Staying)

Variable	Mean Effect	SE
Market Factors		
Population	4.777	.714
Per capita income	−5.292	2.100
Distance	.730	.772
Vacation city	−.025	.179
Gate controlled	−1.175	.357
Slot controlled	−.286	.340
Temporal Factors		
Quarter 1	.149	.230
Quarter 2	−1.157	.178
Quarter 3	−.636	.199
Diffusion–Year 1	2.437	.460
Diffusion–Year 2	1.175	.396
Firm Factors		
Own price	−.291	.095
Price heterogeneity (standard deviation of distribution)	.033	.071
Competitor price	.084	.150
Cost per seat mile	−5.309	.499
Number of major competitors	−.126	.056
Number of discount competitors	−.079	.075
Origin city hub	−.342	.311
Destination city hub	1.551	.336
Number of rivals with hubs	−.161	.065
Carrier size	30.468	3.426

as a proxy for other factors, such as marketing efforts, which may be highest during the first year of the launch of the service.

In Table 3, we also reveal the significant role of several firm factors in determining overall market attractiveness. In particular, we find that the airline's own price has a statistically significant effect, in that a higher price level corresponds to a lower level of attractiveness and a lower probability of staying in the market. The role of price with respect to profitability is twofold; on the one hand, a higher price implies a larger margin and higher profits, and on the other hand, it implies lower demand and lower profits. Our results suggest that the latter effect dominates, at least for our data. Controlling for the extensive heterogeneity in intrinsic attractiveness, we find little heterogeneity in price sensitivity; competitors' average price is not a significant driver. Because our measure is an aggregate across all competitors in a city-pair market, an individual competitor's price may have an effect, but given the range of possible competitors in each market, it becomes infeasible to accommodate their separate effects. As we expected, a higher cost per seat mile for the airline significantly lowers its probability of staying in all the markets in which it competes. We also find that as the number of major competitors in a market increases, the overall attractiveness of the market decreases, which increases the probability of exiting the market (negative coefficient). Airlines that use one of the city-pair markets as a hub are more likely to stay in the market, but if there are more rivals that also use these markets as hubs, the probability of staying declines because the market becomes less attractive to the discount carrier. Finally, we find that overall carrier size has a positive effect on the decision to stay.

We identified the variables with statistically significant effects, but we still must determine whether we can compare the substantive impact of these factors on the probability of staying, and we must compute measures that are comparable across covariates so that we can understand which factor is more important. Accordingly, in Table 4, we present the elasticity estimates for five statistically significant covariates. We provide separate elasticities for all airlines versus ATA to show how they vary across airlines.

We examine the elasticities of two discrete and three continuous variables. The discrete variables are absence (0) or presence (1) of gate control and whether (1) or not (0) the destination city is a hub for the airline. We compute the elasticities by considering the difference in the probability of staying when the variable takes the value of 1 versus 0 and dividing that difference by the probability when the variable takes the value of 0. We then compute the average across all appropriate observations (for the focal airline) (Jain and Vilcassim 1991). The results in Table 4 indicate that the effect of having the destination city as a hub increases the probability of all airlines staying in the market by approximately 10%. However, this effect is somewhat more muted in the case of ATA, for which the probability increases only by 7%. Whether the airport is gate controlled is important in keeping an airline; specifically, the presence of gate controls lowers the probability that an airline will stay by approximately 20%, though again, the effect is lower for ATA, whose probability of staying falls by

TABLE 4
Elasticity Estimates

A: All Airlines

Variable	Probability of Staying in the Market Increases by (%)
Own price (increases by 1%)	−.045
Cost per seat mile (increases by 1%)	−.570
Gate control (0–1)	−19.903
Destination city hub (0–1)	10.264
Number of rivals with hubs (increases by 1)	−1.811

B: ATA

Variable	Probability of Staying in the Market Increases by (%)
Own price (increases by 1%)	−.029
Cost per seat mile (increases by 1%)	−.420
Gate control (0–1)	−10.131
Destination city hub (0–1)	7.248
Number of rivals with hubs (increases by 1)	−1.073

approximately 10%. Overall, the elasticities of the discrete variables for ATA are 50%–70% of the elasticities across all airlines. Furthermore, it indicates that gate control is more important than the hub effect, at least for these data.

Turning to the continuous variables—own price, cost per seat mile, and number of rivals with hubs in either city in the market pair—we calculate the percentage change in the probabilities of staying for a 1% change in the first two variables and an increment of 1 for the third variable. First, elasticities at the 1% change level are much smaller than the discrete variable elasticities. In other words, a price change of far more than 1% is needed to create the same impact on probabilities that a non-gate-controlled, versus a gate-controlled, airport has. Second, a 1% change in cost per seat mile has a greater impact on probabilities than a 1% change in price. Third, increasing the number of rivals with hubs by 1 reduces the probability of staying by approximately 2%. In Table 4, we also illustrate the variation in elasticities across airlines and note that ATA has lower elasticities than those of all airlines in general.

Are market factors more or less influential than firm factors for the decisions of discount airlines to stay in or exit a market (Sheppard 1994)? The proposed model includes both sets of covariates, and we estimate restricted models for each. In both models, firms continue to update their intrinsic attractiveness parameters. The fit statistics of these models also indicate that firm-level factors are more influential in determining overall attractiveness than market-level factors.

Endogeneity Concerns

Two potential sources of endogeneity exist for our analysis. The first is related to the number of competitors in the market, NMC_{imt}. As we noted previously, this variable typically does not vary during a new entrant's tenure in the market and, without loss of generality, can be written as NMC_{im} for airline i in market m. In turn, the error term ε_{imt} in Equation 1 may have a time-invariant component (e.g., ξ_{im}) that is correlated with NMC_{im}. In other words, an unobserved factor that drives a market's attractiveness may determine the number of players that compete in the market. This factor could be demand related or unobserved cost components. If this correlation exists, it can bias not only the parameter for the variable NMC_{im} but also those for other variables, such as price. Similar endogeneity concerns are central to studies that pertain to market entry (e.g., Bresnahan and Reiss 1987). The simplest way to address this issue is to eliminate all variables included in the model that vary only across discount airlines i and markets m but are time invariant and then estimate airline–market fixed effects, which we can do because of the panel nature of our data. The fixed effects "soak up" the effects of not only the time-invariant variables excluded from the model but also the unobserved error term ξ_{im}. Thus, the estimated coefficients for variables such as price will not be contaminated. After we estimate the fixed effects, we can recover the effects of the time-invariant variables by regressing the fixed effects using generalized instrumental variables methods (to account for the potential correlation between, for example, NMC_{im} and ξ_{im}) in a second stage. We conduct this analysis for the subset of markets for which we had at least seven time-series observations; then, we reestimate the original model and the fixed-effects model. We statistically test the difference in the price coefficients for these two approaches and find that the estimated difference is not statistically significantly different from 0 (t-value = 1.14). Although our estimated price parameter is not contaminated, we need a valid instrument for the number-of-competitors variable to carry out the second-stage regression; however, such an instrument is not readily available.

The second potential source of endogeneity occurs if firms drop their prices in anticipation of a market exit, which would correlate prices and some component of the error term in Equation 1. To determine whether this source is an issue, we inspect whether prices in the two months before exit are extreme (i.e., lowest or highest in the time series of prices for that airline market). If this trend occurs for a large proportion of exits, we should be concerned about endogeneity, but extreme prices occur in fewer than 20% of the cases in our data. Although not 0, this proportion nonetheless implies that other reasons explain low or high prices in the time-series data for an airline market. Again, to account for the endogeneity issue explicitly, we would need instruments for prices that are both time varying and airline–market specific, but such instruments are not readily available. Notwithstanding these checks, there could still be unobserved factors that are correlated with the number of competitors in a city market pair or with the prices in a given quarter. To that extent, this possibility would be a research limitation that needs to be more fully addressed in subsequent work.

Model Comparison

The model structure in Equation 3 suggests that a natural alternative to our proposed model is a simple logit model without learning,[10] which would assume that $\bar{A}_{imt} - \bar{\pi}_{im}$ in Equation 3 is A_{im}, or the intrinsic attractiveness of market m to firm i known to the firm (which implies no uncertainty and the absence of a time subscript). Thus, all time-varying factors and time-invariant and other drivers of attractiveness appear as covariates in the X_{imt} and Z_{im} matrices. Another alternative specification would involve a discrete-time semiparametric hazard model that does not impose the learning model on intrinsic attractiveness $\bar{A}_{imt} - \bar{\pi}_{im}$. Instead, the model would include time-specific intercepts to account for the time-varying nature of the firm's exit behavior (see Jain and Vilcassim 1991; Seetharaman 2004; Seetharaman and Chintagunta 2003). Although such a model appears prima facie more flexible than our model, our model structure enables us to include both firm- and market-specific time effects, $\bar{A}_{imt} - \bar{\pi}_{im}$. In contrast, a discrete-time semiparametric specification makes it difficult to account for both market and firm heterogeneity in a flexible manner because of the many parameters that must be estimated.

We estimate these two alternative specifications using the estimation sample and find that in all cases, unobserved heterogeneity is accounted for similarly to our proposed specification. Furthermore, we compute the predictive log-likelihood for all three models for the holdout sample of city-pair markets, as we display in Table 5. For both model fit and predictive ability criteria, our proposed model is superior to the alternative models, largely because the learning formulation accounts for both heterogeneity across airline markets and temporal dynamics in demand. In contrast, the logit model emphasizes heterogeneity, and the hazard model emphasizes the temporal component only.

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[10] We thank an anonymous reviewer for suggesting this comparison model.

Managerial Implications

Our results indicate that (1) firms learn about their markets' true attractiveness over time, (2) a combination of market and firm factors drives the success and failure of discount airlines in the markets they enter, and (3) firm factors are more important than market factors in driving decisions to stay in or exit a market. For communities that want to attract a new discount carrier to operate in their markets, gate controls at the airport strongly influence probabilities of staying. Casual empiricism seems to suggest that communities are concerned about this factor; many communities that build new airports are careful to construct them without significant financial involvement from airlines. This independence lowers their obligation to the airlines in terms of gate allocations, which in turn lowers entry barriers for smaller, discount airlines.

From the perspective of an airline entering the market, our results suggest that prices and costs are important control variables and must be managed carefully to facilitate survival. Furthermore, costs are considerably more important than prices in this regard. The choice of hubs is also crucial to the survival of an airline in a market, so choosing an appropriate hub city should constitute an integral part of the airline's strategic market plan. For example, the main difference between ValuJet's and AirTran's strategies was that ValuJet used Atlanta, the hub of a major carrier (Delta), whereas AirTran moved its hub to Orlando, which is not a Delta hub. Southwest used a similar strategy of flying to secondary airports rather than to airports in which major airlines already dominated. By not competing with the major carriers head-on, discount carriers may have a better chance of success.

Conclusions

We undertook this study in response to a perceived gap in the literature; namely, not enough attention had been paid to understanding the factors that influence firms' exit behaviors. Accordingly, we integrate research perspectives from economics, industrial organization, organizational studies, and strategy literature to understand the various market and firm factors that drive a firm's decision to stay in or exit a market. In the highly competitive airline environment, estimating the intrinsic attractiveness of markets, learning, and exiting from unprofitable markets have become important strategies that affect firm profitability and survival. For a firm entering a new market, it is difficult to make fully informed market entry decisions because markets that may seem lucrative initially may not be in reality (Zajac and Bazerman 1991). Thus, firms must reevaluate their decisions to enter, stay in, or exit a market, and a learning model is well suited for such reevaluations (Biyalogorsky, Boulding, and Staelin 2006; Zajac and Bazerman 1991). Whereas empirical research in marketing has used learning models to understand how consumers update their beliefs (Erdem and Keane 1996), our application involves firm exit decisions using a learning approach. Therefore, we integrate a model of firm learning in the context of other factors that drive a firm's market exit decision, fill a gap in the literature, and answer questions that Zajac and Bazerman (1991) and Biyalogorsky, Boulding, and Staelin (2006) raise to supplement and complement their research.

The key empirical contributions of this article are substantive. Our analysis shows that airlines' prior beliefs about market attractiveness are not necessarily consistent with the market's intrinsic attractiveness. Airlines also seem to learn about true market attractiveness over time. For some airlines that subsequently went bankrupt (e.g., Vanguard), we observe that true market attractiveness was lower than perceived initial attractiveness. Our results also highlight variables that influence exit decisions. In particular, firm-level factors appear more important than market-level factors; specifically, own price, cost per seat mile, and whether the city-pair market includes a hub for the airline are statistically significant. The main market-level factors are gate control, population, and per capita income. We also find that market-level factors, such as distance between cities, do not have a significant impact. As long as other operational elements are well integrated, discount airlines need not restrict their operations to markets with geographic proximity (as long as the same aircraft can be used to service both short and long flights). Taken together, we clarify the effects of marketing variables under the control of the firm (e.g., own price) and those that can be used by the city or airport to market itself to a discount airline (e.g., gate control).

We acknowledge that our findings pertaining to exit behavior are based solely on one industry. Although we

TABLE 5
Model Fit and Predictive Ability

Specification	Parameters	In-Sample Fit –Log-Likelihood	In-Sample Fit BIC	Prediction –Log-Likelihood
Proposed model	57	884	2240	321
Logit model (with heterogeneity)	45	956	2284	335
Hazard model (with heterogeneity)	58	937	2356	344

Notes: BIC = Bayesian information criterion.

believe that our findings can be generalized to other industries (e.g., retailing) and settings (e.g., new product failures), we advise future researchers to draw conclusions based on their specific situations and to the extent to which they find our results generalizable. We also acknowledge that other variables could be important in real-life situations; our learning model is limited to the variables we chose. However, we posit that exit decisions based on our formal model of firm learning, despite the model's limitations, can provide a consistent and viable alternative approach for marketing managers who make exit decisions (Biyalogorsky, Boulding, and Staelin 2006; Bolton 2003; DeGeus 1988). In addition, as we noted, a more careful analysis of endogeneity is warranted for models that mirror ours.

Further research should consider other factors that might influence survival and exit. In a recent study, Robinson and Min (2002) have postulated that firms' order of entry may influence survival. From a modeling perspective, it may also be useful to investigate the consequences of firms' forward-looking behavior. In summary, our study represents a first step toward understanding the exit behavior of discount airlines from city-pair markets in the United States through the use of a learning model.

APPENDIX
Selected Literature on Firm Learning and Market Exit/Failure

Category/Variables	Authors	Industries Studied	Model	Findings and Comments
Behavioral Factors				
Learning process	Day (2002); DeGeus (1988); Garvin (1993); Hill and Hlavacek (1977); Hoch and Ha (1986); Malter and Dickson (2001); Sinkula (1994); Slater and Narver (1995)	Conceptual	Conceptual	Firm learning is a basis of competitive advantage. Firms need to maintain a limited number of ventures at different stages of development and different levels of risk. Sequenced go/no-go checkpoints help firms make decisions.
Demand uncertainty/ pioneers and winner's curse	Chandy and Tellis (2000); Hitsch (2006); Robinson and Min (2002); Tellis and Golder (1996)	Manufacturing New product	Logit regression	Pioneers may face uncertainty but have significantly higher survival rates than early followers, largely due to the first-mover advantage and a temporary monopoly position. Value of reducing uncertainty could be large, and firms should increase new product launch opportunities.
Herd behavior	Kennedy (2002)	Television networks	Simultaneous equations	Television networks pursue strategies similar to those of rivals, which actually lowers ratings but is still pursued.
Competitive blind spots	Zajac and Bazerman (1991)	Conceptual	Conceptual	Managers' competitive blind spots, irrational escalation of commitment, overconfidence in judgment, and limited perspective and frame of the problem may lead to failure.

APPENDIX
Continued

Category/Variables	Authors	Industries Studied	Model	Findings and Comments
Stickier priors/escalation bias	Bolton (2003); Bolton and Reed (2004); Boulding, Morgan, Staelin (1997); Biyalogorsky, Boulding, and Staelin (2006)	Undergraduate students, e-books MBA students, quality valve company case New product	Multivariate analysis of covariance Belief-updating model Experiments	Corrective procedures encourage analytic thinking. Escalation bias in new product introduction. Precommitment to a decision rule is an effective method of reducing commitment to a losing course of action.
Consumer learning models	Erdem and Keane (1996); Narayanan, Manchanda, and Chintagunta (2005); Roberts and Urban (1988)	Consumers Physicians	Bayesian learning	Consumers learn about the quality of packaged goods over time; detailing and persuasive roles of information on physicians prescriptions.
Firm Effects				
Firm size and economies of scale	Audretsch, Houweling, and Thurik (2000); Ghemawat and Nalebuff (1990); Klepper (1996)	Manufacturing and other	Profit functions Logit regression Duopoly and oligopoly model using game theory	As firms grow in size, they spend more on sunk costs (research and development, advertising, and marketing). Smaller firms have a longer payback period, which negatively affects profitability. Larger firms at entry find it easier to survive. Larger firms can increase their survival by closing plants.
Firm age	Thornhill and Raphael (2003)			Younger firms are more prone to failure because of differences in knowledge.
Cost and price	Dixit (1989); Klepper (1996)		Derivative functions	The ideal exit trigger price is the price that is less than the variable cost minus the interest on the exit cost. Economic factors include market price variables, cost of capital, sunk costs, and lump-sum exit costs.
Macroeconomic and Market Effects				
Business cycles	Campbell (1998)	Manufacturing	Extended vintage capital model	Cycles can be linked to entry and exit.

APPENDIX
Continued

Category/Variables	Authors	Industries Studied	Model	Findings and Comments
Demand conditions	Asplund and Sandin (1999); Audretsch and Mahmood (1995); Caballero and Hammour (1994); Ghemawat and Nalebuff (1990); Van Kranenburg, Palm, and Pfann (2000)	Swedish beer market Manufacturing Daily newspapers	Weibull distribution model Hazard (Cox) model Hazard rate and exponential model	High failure rates may be related to uncertain consumer reception of new products. Hazard rates are higher during periods of unemployment. Drops in demand cause outdated plants to become unprofitable and likely to exit in a recession. Shrinking demand creates pressure to reduce capacity. The largest firms exit first. Exit rates are inversely related to variations in real income per household.
Technology Improvements	Audretsch (1991); Campbell (1998); Jovanovic and McDonald (1994)	Industrial firms Manufacturing Automobile tires	Logit regression Extended vintage capital model Profit function showing time paths	In a routinized technological regime, small firms are at a disadvantage, and their survival rate is distinctly lower. Embodied technology induces obsolete plants to cease production. Firms unable to adjust to a new regime exit the market.
Competitive Intensity and concentration	Agarwal and Gort (1996); Seim (2004)	Manufacturing Video retailers	Derivative function, moving average Simulation location choice model	Concentration intensifies competition, and only the fittest incumbents survive. Firms shield themselves from most competition by increasing spatial distance.
Industry growth	Ilmakunnas and Topi (1999); Mata, Portugal, and Guimaraes (1995)	Manufacturing	Poisson and negative binomial model Econometric duration models	Increase in number of firms increases industry size, which is related to higher exit rates. New plants are likely to survive longer in growing industries. Larger plants are less likely to die.

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Remco Prins & Peter C. Verhoef

Marketing Communication Drivers of Adoption Timing of a New E-Service Among Existing Customers

This study investigates the effects of direct marketing communications and mass marketing communications on the adoption timing of a new e-service among existing customers. The mass marketing communications pertain to both specific new service advertising and brand advertising from both the focal supplier and the competitors. Using a split-hazard approach, the authors determine the effects of the considered marketing communications on adoption timing, accounting for a significant part of the customer base that never adopts the new e-service. They analyze individual adoption behavior with a sample of 6000 customers of a Dutch telecommunications operator over 25 months. The empirical results show that service advertising shortens the time to adoption, even when it is initiated by competitors. Furthermore, an exploratory analysis of the interaction effects between relationship characteristics and marketing efforts suggests that certain mass marketing efforts have a greater effect on loyal customers.

Successful new product/service introductions are important for a firm's long-term performance. This especially holds for industries in which firms invest heavily in technologies, such as mobile networks, under the premise that firms will be able to introduce new services using these technologies. For example, in Europe, telecommunications firms invested heavily in licenses for UMTS (Universal Mobile Telecommunication System) networks, paying €109 billion to the owners (i.e., the government) of these networks, in the hope that new 3G (third-generation) services would cause the saturated mobile telecommunications market to grow again (*The Economist* 2004). It soon became clear that the expectations about the UMTS technology were too high and that the actual rollout of 3G services would take several years longer. As a consequence, market values of telecommunications firms dropped considerably (Van Damme 2002). To get return on this type of technological investment, the new services based on the new technology should be successfully introduced. To achieve this, service providers must formulate an introduction strategy that focuses on both existing customers and potential new customers. Existing customers may be the most important target group for newly introduced products or services because they may be more likely to adopt the innovation as a result of their positive attitude toward the firm.

There is a large research stream in the marketing literature on new product adoption or trial by consumers (Meuter et al. 2005; Rogers 1995; Steenkamp and Gielens 2003). An important characteristic of this research stream is that it usually studies the adoption of new products or services in the total market, which consists of both existing customers and noncustomers. So far, researchers have not studied the adoption of new products or services among existing customers only. Moreover, many companies now consider their existing customers assets, which is reflected in the increasing importance of customer management in many industries (e.g., Boulding et al. 2005). From a customer management perspective, the cross-selling of new services to current customers can be a good strategy to increase the value of the customer base. If current customers adopt the new service, their customer lifetime value (CLV) should increase (Bolton, Lemon, and Verhoef 2004; Gupta, Lehmann, and Stuart 2004; Hitt and Frei 2002; Hogan et al. 2002; Rust, Zeithaml, and Lemon 2000), as long as the new service does not fully replace an existing one. Both the adoption itself and the timing of adoption are relevant in terms of a higher CLV because increased cash flows from a new product adoption occur earlier in the relationship, and prices of new services are often higher in the early stages of the product life cycle. In this study, we investigate marketing communication drivers of the adoption timing of a new e-service among existing customers.[1] We aim to contribute to both the adoption and customer management literature.

It is important to consider the difference between cross-buying or add-on buying of services and adoption of a new service among existing customers because it could be

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[1] Given our empirical focus on new service adoption, we mainly use the term "service" when discussing adoption. However, the theoretical discussion holds for both services and products.

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argued that new service adoption and cross-buying of additional services are the same insofar as both pertain to relationship expansion through buying more services (e.g., Verhoef, Franses, and Hoekstra 2001). However, there are some fundamental differences. First, cross-buying pertains to services that are already mature and known to the customer, whereas new service adoption involves products or services that are new to the world. This newness makes it a different buying decision because there is much more uncertainty about the characteristics and the usefulness of the new service. Second, cross-buying may also imply switching a service (e.g., a car insurance) from a competitor to the focal firm, whereas new product adoption implies buying a newly introduced service that is not yet purchased from competitors. Third, whereas cross-selling of services mainly focuses on existing customers through, for example, direct mailing and telemarketing (e.g., Verhoef, Franses, and Hoekstra 2001), the introduction of new services concerns the introduction both to the existing customers and to the total market. This causes large differences in the marketing communications that are used. Whereas cross-selling strategies mainly use below-the-line advertising, new product introductions may use both mass marketing communications and below-the-line advertising.

We contribute to the adoption literature as follows: First, this is the first study that considers the adoption timing decision solely among existing customers. Second, we broaden the scope of studied marketing communication drivers. In general, adoption studies consider the impacts of innovation characteristics, such as relative advantage, ease of use, risk, and complexity, and consumer characteristics, such as demographics and innovativeness (e.g., Arts, Frambach, and Bijmolt 2005; Manning, Bearden, and Madden 1995; Steenkamp and Burgess 2002). Recently, Steenkamp and Gielens (2003) have included (time-varying) marketing and communication efforts, such as advertising and promotions, as predictors of new product adoption in a consumer packaged goods context. However, attention to the impact of marketing communication efforts on new product or service adoption remains limited. In general, studies have ignored (1) the impact of individual-oriented marketing communication efforts (or direct marketing communications), such as direct mailings and e-mails; (2) the differential impact of marketing communication efforts that are specifically focused on the new product/service and those at the brand/company level;[2] and (3) the impact of competitive marketing communication at both the new product/service and the brand/firm level.

We contribute to the customer management literature as follows: First, new product adoption as a driver of customer equity has been almost completely ignored. For example, Bolton, Lemon, and Verhoef (2004) focus only on customer retention, service usage, and cross-buying as components of CLV in their CUSAMS (customer asset management of services) framework. Hogan and colleagues (2002) merely conceptually acknowledge the importance of new product adoption for customer profitability and CLV. Empirically, Hogan, Lemon, and Libai (2003) relate service adoption behavior to CLV and state that defecting new product adopters have a significant, negative impact on customer equity because of negative word of mouth. Recently, Kamakura, Kossar, and Wedel (2004) have developed a methodology to identify new product adopters for cross-selling purposes, using data on prior behavior as predictors, but they do not theoretically focus on drivers of new service adoption. Second, studies of the predictors of customer behavior mainly consider individual-oriented or customer-specific marketing interventions, or below-the-line advertising (Venkatesan and Kumar 2004). In this study, we include not only customer-specific marketing interventions but also above-the-line advertising expenditures over time, which do not vary across customers. As Bolton, Lemon, and Verhoef (2004) note, in general, advertising is associated with mass marketing, but Ambler and colleagues (2002) argue that brand advertising may increase the value of existing customers as well. Empirical evidence for this effect from advertising data remains scarce. Third, most studies in the customer management area do not include competitive instruments, though understanding customer responses to competitive actions is essential (Keiningham, Purkins-Munn, and Evans 2003). Therefore, we explicitly account for the effect of competitive advertising on individual customer adoption.

We organize the remainder of this article as follows: We begin with a discussion of our conceptual model, which we apply in the context of customer adoptions of a new e-service. Subsequently, we discuss our model to explain adoption timing. Note that we use a split-hazard model, which jointly models antecedents of the adoption probability and adoption timing. Then, we present the empirical results and key findings pertaining to the impact of various types of mass advertising on adoption timing and the different effects of customer-specific antecedents on adoption probability and timing. In addition, we report some significant interaction effects between mass marketing efforts and customer behavior. We conclude with a discussion of the findings, implications, and limitations of our study.

Conceptual Model and Hypotheses

We display our conceptual model in Figure 1. In this model, we study the effect of marketing communication efforts on the adoption timing of a new service. We define "adoption timing" as the time between the introduction and the adoption of the new service (Steenkamp and Gielens 2003). In this context, we define "adoption" as the actual buying of the new service by an existing customer. In our empirical model, we view adoption timing as conditional on adoption. We discuss this issue in greater detail in our "Methodology" section. In our model, the main focus is on the effect of marketing communication efforts because many studies in the new product diffusion literature have already shown that marketing efforts can have a significant effect on adoption rates at the aggregate level (Bass, Krishnan, and Jain 1994; Horsky and Simon 1983; Kalish 1985; Simon and Sebastian

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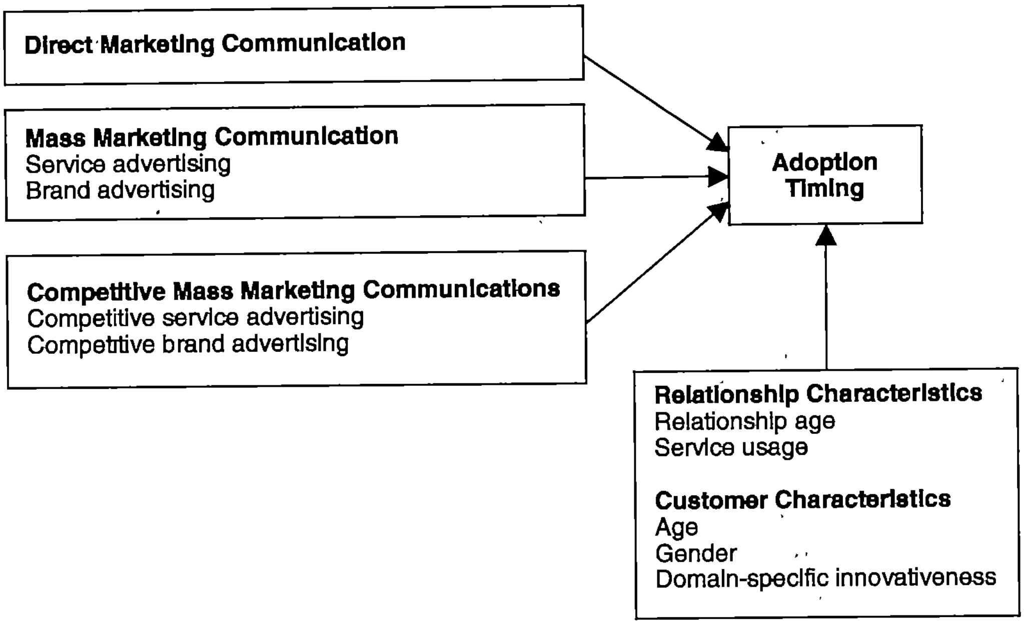
[2] Note that this distinction is especially important for multiproduct or service firms, which advertise their brand (and a portfolio of offered products or services) and their newly introduced service to both potential and current customers.

FIGURE 1
Conceptual Framework


Direct Marketing Communication
Mass Marketing Communication
Service advertising
Brand advertising
Competitive Mass Marketing Communications
Competitive service advertising
Competitive brand advertising
Adoption Timing
Relationship Characteristics
Relationship age
Service usage
Customer Characteristics
Age
Gender
Domain-specific innovativeness

1987). We consider three groups of marketing communication variables that potentially explain adoption timing: (1) direct marketing communication efforts to existing customers pertaining to the new service, (2) mass marketing communication efforts (i.e., advertising) at the new service level and at the brand/firm level, and (3) competitive mass marketing communications at the new service level and at the brand/firm level. We also include a set of covariates to control for customer specific effects—namely, relationship characteristics (i.e., relationship age, service usage) and customer characteristics (i.e., age, gender, innovativeness).

Direct Marketing Communication

Direct marketing communications focus mainly on directly influencing existing-customer buying behavior (e.g., by providing attractive offers) and are essentially transaction oriented (Rust and Verhoef 2005). The effect of direct marketing communication on customer buying behavior has only recently gained attention in the academic marketing literature. Verhoef (2003) shows that direct marketing communication increases customer share. Venkatesan and Kumar (2004) report initial positive effects for reasonable amounts of direct marketing communications on purchase frequency, which become negative for large amounts of direct marketing communications (inverted U-shaped effect). Verhoef, Franses, and Hoekstra (2001) report positive effects of direct marketing communication on cross-buying. In the adoption literature, attention to direct marketing communication is lacking because of its focus on adoption behavior in the total market. Steenkamp and Gielens (2003) study other below-the-line actions, such as promotions, and show that these positively affect individual trial probabilities for consumer packaged goods. Together, these studies suggest that direct marketing communication focuses existing customers' attention on the new service, which may have a direct impact on their adoption behavior with respect to this new service. Thus:

H_1: Direct marketing communication efforts shorten customers' time to adoption.

Mass Marketing Communication

Within the innovation diffusion/adoption literature, advertising is considered an important marketing tactic to diffuse the innovation in the market (e.g., Bass, Krishnan, and Jain 1994; Kalish 1985). On the individual consumer level, Steenkamp and Gielens (2003) show that mass advertising accelerates adoption among individual consumers. In general, advertising may create awareness and knowledge of the new service among both existing customers and other consumers. Next to awareness, advertising may also aim to inform potential adopters about the advantages of the new service, which may induce adoption. This will all be predominantly accomplished through advertising that specifically mentions the new service (i.e., new service advertising). Given the strong empirical results in the innovation/adoption literature, new service advertising most likely shortens adoption timing. However, as we noted previously, this literature studies all consumers and does not distinguish between existing customers and noncustomers.

Customer management researchers investigating antecedents of customer behavior usually do not include mass advertising efforts as a potential antecedent. A notable exception is Rust, Zeithaml, and Lemon's (2000) customer equity framework, which acknowledges the effect of branding on customer equity. However, in their modeling framework, they include both existing customers and noncustomers. The absence of the effect of mass advertising is explained by two reasons. First, from a data perspective, mass advertising data are not collected in customer databases, because they are available only at an aggregate weekly or monthly level. As a consequence, time-series data on customer behavior are required (i.e., per month) to match these aggregated advertising data. These data should be integrated with data from customer databases. Second, from a theoretical perspective, researchers have assumed that the behavior of existing customers is predominantly affected by company behavior within the customer relationship. Advertising plays a role mainly in attracting new customers (e.g., Bolton, Lemon, and Verhoef 2004). This might be true for behavior such as customer retention and cross-buying, but for newly introduced services, awareness should also be created among existing customers, and information on this new product should also be communicated to existing customers. This might be done through direct marketing communications. In addition, existing customers are likely to be confronted with mass advertising that promotes the new service, which should at least have some effect on customer behavior, in line with diffusion research. On the basis of this discussion, we hypothesize the following:

H_2: Service advertising shortens customers' time to adoption.

Firms not only advertise newly introduced services but also continue their brand-focused advertising efforts. This brand advertising mainly aims to increase brand awareness; to improve brand attitudes; and to affect purchasing behavior, such as brand choice (e.g., Lodish et al. 1995; Rossiter and Percy 1997; Vakratas and Ambler 1999). The question is whether this brand advertising also positively affects the adoption of newly introduced services. An argument in favor of an effect is that brand advertising creates a more positive attitude toward the brand, which may positively affect the attitude toward the newly introduced service, which in turn may positively affect adoption behavior. In the same vain, Verhoef, Franses, and Hoekstra (2002) show that customers who are committed to the firm are more likely to buy additional services. However, we expect that the size of this effect is significantly smaller than the effect of specific service advertising, which directly aims to improve awareness for the new service and attitudes toward the brand. Thus:

H_3: Brand advertising shortens customers' time to adoption.

H_4: Service advertising shortens customers' time to adoption more than brand advertising.

Competitive Mass Marketing Communication

New services are usually not introduced by a single firm in the market. Competitors may introduce a similar service as well. These competitors also advertise their new service to stimulate adoption. Within the diffusion literature, particular attention has been given to the effect of this competitive advertising. It might be assumed that competitive service advertising negatively affects the adoption of the new service among existing customers of the focal supplier, but within the diffusion literature, there is ample evidence that competitive new service advertising may work positively. Indeed, it may even accelerate individual adoption through the market-making effect; that is, the advertising efforts of all competitors increase the penetration rate of new services (Krishnamurthy 2000; Krishnan, Bass, and Kumar 2000). Because of this higher penetration rate, competitors benefit from one another's advertising efforts pertaining to the new service, particularly in new markets with relatively few competitors (Mahajan, Sharma, and Buzzel 1993). Thus:

H_5: Competitive service advertising shortens customers' time to adoption.

As does the focal supplier, competitors may also continue their brand advertising. Similar to the focal suppliers' brand advertising, competitive brand advertising aims to create awareness of the competing brand, to enhance positive attitudes toward the competing brand, and to affect buying behavior with respect to the competing brand. A possible consequence of competitive brand advertising is the enhancement of positive attitudes toward the competing brand among existing customers of the focal firm; it may also decrease brand attitudes toward the focal suppliers. In turn, this might negatively affect adoption. However, so far, evidence for these described effect paths is almost absent in the marketing literature. In their customer equity model, Rust, Zeithaml, and Lemon (2000) assume that when a firm increases its advertising, it creates higher perceived brand equity through increased brand awareness and positive attitude creation, which should lead to higher choice shares for the focal supplier and to lower choice shares for competing suppliers. Whether such an effect might also occur for new service adoption is an empirical question. However, for now, we formulate a hypothesis that is in line with our reasoning:

H_6: Competitive brand advertising lengthens customers' time to adoption.

Interaction Effects Between Marketing Communication Efforts

In addition to the direct effects of these explanatory variables, we explore the interaction effect between direct marketing communication and mass marketing communication. Previous research (e.g., Naik and Raman 2003; Schultz, Tannenbaum, and Lauterborn 1993) points to a synergy between different marketing communication types (i.e., direct marketing communication and mass marketing communication), which should be reflected in a positive interaction effect. This positive interaction effect may occur, for example, because mass marketing communication, which creates awareness and positive attitudes for the new service, increases the effect of direct marketing communication. We have no reason to expect that there will be differences in these effects between service and brand advertising.

H_7: There is a positive interaction effect between direct marketing communication and service advertising.

H_8: There is a positive interaction effect between direct marketing communication and brand advertising.

Covariates

On the basis of prior research in the adoption and customer management literature, we include two groups of covariates in our model: relationship characteristics and customer characteristics. We view the relationship's length and depth as relationship characteristics (Bolton, Lemon, and Verhoef 2004). Several researchers have pointed out that relationship length may affect customer behavior (Dwyer, Schurr, and Oh 1987; Hitt and Frei 2002). However, this relationship may be nonlinear (Bolton, Lemon, and Verhoef 2004; Hitt and Frei 2002). In general, relationship depth, often referred to as "usage intensity" or "category usage," is considered an antecedent of trial or adoption probability (e.g., Steenkamp and Gielens 2003). Consumers who display high category usage levels have a greater category need and, therefore, a higher trial probability for a new product within that category (Gatignon and Robertson 1991). Again, there may be some nonlinearities in this relationship due to customer life-cycle effects (Bolton, Lemon, and Verhoef 2004).

The included relationship characteristics are of interest not only because of possible direct effects on adoption timing but also because there might be some interaction effects between relationship characteristics and communication efforts. Empirical research by Rust and Verhoef (2005) indicates significant heterogeneity of responses to marketing interventions that may be related to relationship characteristics. In particular, we explore the interactions between relationship age and direct marketing communication, (competitive) service advertising, and (competitive) brand advertising. Although the investigation of these interactions is not the primary objective of this study, we believe that it might provide valuable insights into the effects of marketing communication efforts on adoption, which could be studied in-depth in further research.

The customer characteristics we include as covariates are age, gender, and domain-specific innovativeness. These customer characteristics are likely to be important in the adoption probability and timing of individual customers (Arts, Frambach, and Bijmolt 2005). For example, in general, early adopters tend to be younger (Meuter et al. 2005; Rogers 1995). Customer innovativeness is also often considered an important antecedent of new product adoption. Most studies (e.g., Im, Bayus, and Mason 2003; Midgley and Dowling 1993; Steenkamp, Ter Hofstede, and Wedel 1999) focus on innate innovativeness as an individual trait that can be generalized over product categories and find that innovative people have a higher tendency to adopt new products and to adopt them faster. Citrin and colleagues (2000) and Goldsmith, Freiden, and Eastman (1995) show that domain-specific innovativeness, which reflects the consumer's tendency to try the latest innovations in a product category, has a stronger relationship to individual adoption behavior than does innate innovativeness. Our data provide information on the adoption of a previously introduced new service, which may be an indicator of domain-specific innovativeness. Thus, we control for domain-specific innovativeness in our model.

Data Description

Our empirical study focuses on the adoption process of a new mobile e-service in the Dutch consumer market, which a leading Dutch mobile telephone provider introduced in 2002. The new service uses GPRS (General Packet Radio Service) technology to give subscribers access to a range of Web sites specifically designed for mobile telephone use. For our empirical analyses, we employ the service provider's customer database, from which we gather monthly data on mobile subscribers, starting with the introduction date of the new service. These data include information on demographics, usage levels of various services, relationship characteristics, and marketing communication efforts by the provider. After the introduction of the new e-service, every customer could subscribe to it, in addition to their regular subscription with the mobile telephone operator. For each adopting customer, we know the first usage date of the new service, which enables us to determine the individual adoption times for customers who adopted the new service during the observation period.

We chose to study adoption timing in this specific industry, for this specific company, and for this specific service for the following reasons: First, the telecommunications industry is known to collect data continuously on customer behavior in large databases, which enables us to study actual adoption behavior instead of reported or intended adoption behavior for existing customers. Second, the telecommunications industry has been a subject of research in prior adoption/diffusion and customer management research studies (i.e., Bolton 1998; Bolton and Lemon 1999; Simon and Sebastian 1987). Third, this industry is important in today's economies and is continuously introducing new services. Fourth, the introduction of this type of service is managerially relevant because these firms introduce the new services to get returns on their investments in technological networks. Fifth, this company was the first in the Netherlands to introduce this service; thus, the introduced service is fully new to the market. Finally, more from a practical standpoint in conducting successful collaborative research, there is a requirement to work closely with firms, which was possible with this firm because of positive previous experiences.

Sample

For our analyses, we randomly selected 6000 mobile subscribers from the provider's customer database who were current customers at the start of the observation period, which ran from August 2002 ($t = 1$) to August 2004 ($t = 25$). The start of the observation period is marked by the introduction date of the new service. By the end of the observation period, the number of existing customers adopting the new service rapidly declined (see Figure 2). Thus, we expect that the chosen observation period will capture the effects on adoption timing for most existing customers. Although all customers were with the provider at the start of the observation period, 910 left the provider before the end of the period. To avoid a selection bias, we did not exclude these customers from our sample.[3]

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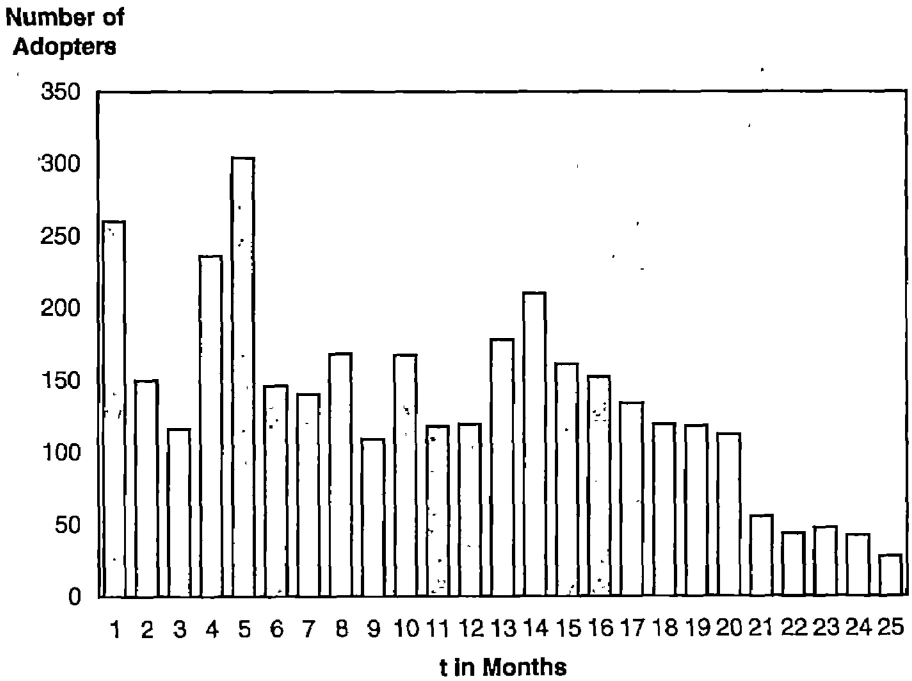
[3] Switchers to the competitive entrant's new service could have caused some of the defections, so these customers would be labeled as nonadopters even though they actually adopted the competitor's new service. Although no data were available on this issue, we believe that it is justified to label these customers as nonadopters because we specifically investigate the adoption of the focal company's new service among existing customers.

FIGURE 2
Monthly Adoptions in Sample



We were confronted with the issue of a relatively small adoption rate, which is not uncommon for multigenerational products or services because the users of the older technology will not immediately adopt the new one (Mahajan and Muller 1996; Pae and Lehmann 2003). It may take a significant amount of time before the diffusion of a new product really takes off (Golder and Tellis 1997; Tellis, Stremersch, and Yin 2003). Because we were particularly interested in the adoption of the new service but only a small portion of customers had adopted the service before September 2004, we oversampled these adopting customers. In our procedure, we oversampled the number of adopters so that approximately half the sample adopted the new service during the observation period, which gave us 3431 adopting customers, or 53% of the sample. Donkers, Franses, and Verhoef (2003) demonstrate that oversampling a rare event in binary choice models does not affect the parameter estimates or their standard errors, as long as the oversampling is not accompanied by stratified sampling on the independent variables. So far, no statistical research has shown that oversampling has an effect on the parameter estimates and standard errors of the split-hazard model. Thus, it is not clear what the effect of oversampling is on the split-hazard model results. Therefore, we estimated models with a smaller fraction of adopters. These models showed similar results in terms of sign and significance of the coefficients. However, models with few adopters have convergence problems, so we also estimated normal hazard models with different fractions of adopters. These results show that the sign of the coefficients do not change. For rather small fractions, however, a smaller number of variables becomes significant because of sample size effects. These additional analyses provided us with sufficient confidence in our estimation results.

Measures

Time to adoption. For each month in our observation period, we observed whether a customer adopted the new service. The time to adoption for each customer represents the time elapsed in months since the introduction of the e-service. We use the individual time to adoption as our observed dependent variable.

Marketing communication variables. During the observation period, the provider selected customers who would receive an individual offer by telephone to adopt the new service. Our data indicate whether and when each customer received an offer call from the provider. We operationalize these data by including a dummy variable that indicates the months in which the customer received the offer. Some customers who did not respond to the first offer were subsequently selected for a second offer. Although we recognize that the provider may have selected only those customers who were most likely to adopt in the first place, which would cause an endogeneity problem, we believe that by incorporating all possible selection criteria into our model, we can avoid serious problems in estimating the effect of direct marketing communication (Franses 2005; Shugan 2004).

We use data pertaining to monthly advertising expenditures to account for advertising effects on adoption timing. We retrieved these advertising data from BBC, a Dutch division of Nielsen Media Research International. Furthermore, we distinguish among service advertising, brand advertising, competitive service advertising, and competitive brand advertising for television, radio, print, outdoor, and cinema. We define "service advertising" as the provider's monthly expenditures (in millions of euros) on advertising that explicitly features the new e-service. In all cases, these advertisements mention the brand name of the provider as well, but the main focus is on the new service. We define "brand advertising" as the provider's expenditures on advertising that is not directly related to the new e-service.

Although the e-service was new to the market at the time of introduction by the provider, six months later, one of its competitors launched a similar service. Therefore, we include "competitive service advertising," or the competitor's advertising that explicitly features a similar e-service. Again, the competitor mentioned its brand name in all these advertisements. Finally, we include "competitive brand advertising," which is all competitors' advertising that is unrelated to any similar e-services. To allow for possible lagged advertising effects, we also include all advertising expenditures in the previous month.

Covariates. As noted, we include relationship age and service usage as covariates. We define relationship age as the number of years the customer had been with the provider at t = 1, the start of the observation period. To measure the service usage, we compute the average monthly amount spent by each customer over his or her total customer lifetime before the start of the observation period. Thus, service usage does not include usage of the newly introduced e-service.

The customer demographics we control for are gender and age. We set the gender dummy to zero for male customers, and we define the age variable as the customer's age in years at the start of the observation period, so that it is fixed over time. As a proxy for the domain-specific innovativeness of each customer with respect to mobile e-services, we include a dummy variable that indicates the adoption and use of a prior generation mobile e-service, which was introduced several years before. Table 1 summarizes and describes all our included variables.

TABLE 1
Measurements and Descriptives of Explanatory Variables

Variable	Label	Average	SD
Marketing Communication			
Direct Marketing Communication Dummy for individual offer by telephone for customer i in month t	DMC_{it}	.09	.13
Mass Marketing Communication			
Service Advertising Advertising expenditures in millions of euros in month t related to the new service	SA_t	1.11	.88
Brand Advertising Advertising expenditures in millions of euros in month t not related to the new service	BA_t	1.50	1.05
Competitive Mass Marketing Communications			
Competitive Service Advertising Advertising expenditures of all competitors in millions of euros in month t related to a similar service	CSA_t	.95	1.12
Competitive Brand Advertising Advertising expenditures of all competitors in millions of euros in month t not related to a similar service	CBA_t	6.23	2.44
Relationship Characteristics			
Relationship Age Number of years customer i has been with the provider at t = 1	RA_i	2.67	1.65
Service Usage Average monthly amount spent by customer i before t = 1	SU_i	3.39	4.03
Customer Characteristics			
Gender (male = 0, female = 1)	$Gend_i$	.26	.43
Age At t = 1	Age_i	37.93	10.45
Domain-Specific Innovativeness Dummy for usage of prior generation e-service by customer i	$Innov_i$	.03	.18

Methodology

Adoption studies that consider adoption a discrete event use a logit or probit-like model to assess the impact of independent variables on adoption (e.g., Meuter et al. 2005), whereas those that investigate adoption timing tend to use a hazard model (e.g., Steenkamp and Gielens 2003). The hazard model makes the assumption that, eventually, every consumer will adopt the new product. Especially for products and services with greater technological complexity, a significant group of consumers will never adopt. Theoretically, this issue has been pointed to as innovation resistance and is reflected in rejecting the new service, opposing the new service, or postponing the adoption of the new service (e.g., Bagozzi and Lee 1999; Mittelstaedt et al. 1976; Ram and Sheth 1989; Szmigin and Foxall 1998). For example, this innovation resistance may be caused by consumers being comfortable with the current situation, not perceiving the advantage of the new service, or considering it a risky innovation. Sheth (1981) concludes that consumers who resist innovations tend to be different from consumers who do not resist innovations.

The notion that a group of customers will probably never adopt the new service has important implications in the study of the antecedents of adoption timing. Not only are these consumers unaffected by the time elapsed after the introduction of the product, but we also assume that they are "immune" to any marketing efforts. In other words, the probability of adoption for these consumers is zero. A traditional hazard approach does not account for this group, because it assumes that all consumers are "at risk" for adoption after the product's introduction. In practice, we cannot observe whether a consumer belongs to the immune group, but we can estimate the probability of eventual adoption by each consumer using available customer characteristics.

The econometric model accounting for the problem—that a significant portion of the consumers will never adopt—emerges through the split-hazard approach. Developed by Schmidt and Witte (1989), this split-hazard approach has been applied in various contexts, including new product adoption (e.g., Chandrashekaran and Sinha 1995; Dekimpe et al. 1998; Kamakura, Kossar, and Wedel 2004; Sinha and Chandrashekaran 1992). Following this methodology, we apply a split-hazard approach to model both the adoption probability and the adoption timing of the new service by existing customers. Thus, the time to adoption for individual i, denoted as T_i, is a random variable with a cumulative distribution function F(t) and density f(t) = F′(t). The probability that adoption has not yet occurred at time t is provided by the survivor function S(t) = 1 – F(t). The hazard rate h(t) = f(t)/S(t) can be defined as the conditional likelihood that adoption will occur at time t, given that adoption has not occurred yet. We can observe adoption only for the consumers who adopted within the period of observation (0, T); those who did not adopt before time T will either be censored and adopt at some time beyond T or never adopt at all. The split-hazard model enables us to estimate simultaneously the probability of eventual adoption and the time to adoption. We include a dummy variable that indicates adoption by the end of the month in the hazard part of our model as the failure indicator. Customers are considered at risk of adoption as long as they have not adopted the new service. Those customers who left the provider during the observation period can be included in the analysis only for the periods in which they remained with the company.

We model adoption timing as a hazard function of both time-varying marketing communication efforts and the time-invariant covariates (i.e., relationship characteristics and customer characteristics). The baseline hazard function follows a prescribed distribution and captures the longitudinal regularities in adoption time dynamics, separate from the effects of the covariates. In other words, it captures the effect of the time elapsed since the introduction of the new product. The parametric form we use for our hazard function is the complementary log-log model, which is particularly useful when data from discrete time intervals are used for a continuous underlying adoption process because the estimates of the model do not depend on the length of the time intervals (Allison 1982; Van den Bulte and Lilien 2001). To account for (nonlinear) time dependencies of the baseline hazard rate, we include a time-trend variable and the squared time trend in the hazard part of our model. Higher-order transformations result in significant coefficients but capture too much of the effects of the time-varying variables, such as advertising effects. Therefore, we allow only for a first- and second-power time dependency of the baseline hazard in our model.

We represent the hazard part of our model, including all explanatory variables, as follows:

$$
\begin{aligned}
(1)\quad h_{it} = 1 - \exp[-\exp(&\beta_0 + \beta_1 \times t + \beta_2 \times t^2 + \beta_3 \times \mathrm{DMC}_{it}\\
&+ \beta_4 \times \mathrm{SA}_t + \beta_5 \times \mathrm{SA}_{t-1} + \beta_6 \times \mathrm{BA}_t + \beta_7 \times \mathrm{BA}_{t-1}\\
&+ \beta_8 \times \mathrm{CSA}_t + \beta_9 \times \mathrm{CSA}_{t-1} + \beta_{10} \times \mathrm{CBA}_t\\
&+ \beta_{11} \times \mathrm{CBA}_{t-1} + \beta_{12} \times \mathrm{RA}_i + \beta_{13} \times \mathrm{RA}_i^2 + \beta_{14} \times \mathrm{SU}_i\\
&+ \beta_{15} \times \mathrm{SU}_i^2 + \beta_{16} \times \mathrm{Age}_i + \beta_{17} \times \mathrm{Age}_i^2 + \beta_{18} \times \mathrm{Gend}_i\\
&+ \beta_{19} \times \mathrm{Innov}_i)].
\end{aligned}
$$

Simultaneously, we estimate the unobserved probability of eventual adoption for every individual customer, which we denote as p_i. We model the probability of eventual adoption as a logit function of time-invariant customer characteristics and relationship characteristics:

$$
\begin{aligned}
(2)\quad p_i = 1/[1 + \exp(&\gamma_0 + \gamma_1 \times \mathrm{RA}_i + \gamma_2 \times \mathrm{RA}_i^2 + \gamma_3 \times \mathrm{SU}_i\\
&+ \gamma_4 \times \mathrm{SU}_i^2 + \gamma_5 \times \mathrm{Age}_i + \gamma_6 \times \mathrm{Age}_i^2 + \gamma_7 \times \mathrm{Gend}_i\\
&+ \gamma_8 \times \mathrm{Innov}_i)].
\end{aligned}
$$

The log-likelihood function of our total model (including Equations 1 and 2) is as follows:

$$
\begin{aligned}
(3)\qquad \mathrm{LL} = \sum_{i=1}^{N} &d_i \times \ln\left[p_i \times h_{it} \times S_{it-1}\right]\\
&+ (1 - d_i) \times \ln\left[(1 - p_i) + p_i \times S_{it}\right],
\end{aligned}
$$

where

h_{it} = hazard rate from Equation 1,
p_i = probability of eventual adoption from Equation 2,
d_i = censoring indicator (1 if observed, and 0 if censored), and
S_{it} = survival rate.

For observed adoptions, the censoring indicator d_i equals 1. The contribution to the likelihood function by consumer i at time t is the probability that he or she will eventually adopt, as given by p_i, multiplied both by the conditional probability of adoption at t, as given by the hazard rate h_{it}, and by the probability that he or she has not adopted before t, as given by the survival rate S_{it-1}. Censored observations, for which d_i is 0, belong to either the nonadopters, with probability $(1 - p_i)$, or those who will eventually adopt but have not yet, given by the terms $p_i \times S_{it}$. To obtain the coefficients for every explanatory variable, we use maximum likelihood estimation in STATA Version 8.2.

Results

To assess whether the split-hazard model is required, because we assume that a significant part of the existing customers will probably never adopt the new e-service, we also estimated an ordinary proportional hazard model. Note that these models are nested. When we compare the fit of our split-hazard model with the proportional hazard model, it shows that our model has a significantly better fit, according to the likelihood-ratio test: $\chi^2(9) = 27.546$, $p < .01$. Furthermore, the Akaike information criterion (AIC) statistic of the split-hazard model is smaller (27,229.89 versus 27,239.44), which indicates a better fit. The Bayesian information criterion (BIC) statistic does not show an improvement, which would imply that the split-hazard model does not do a better job in explaining adoption timing than the ordinary hazard model. Note that the BIC penalizes more complex models more heavily than the AIC. However, on the basis of our theoretical justification of the split-hazard approach in the "Methodology" section and of the other diagnostics, we believe that the split-hazard model is theoretically the best way to model individual adoption timing (see also Kamakura, Kossar, and Wedel 2004). Moreover, according to the STATA program, it is rather difficult for the more complex split-hazard model to deliver a better fit. Still, two of our three fit measures favor the split-hazard model. Thus, we discuss only the results of the split-hazard model. The ordinary hazard model does not lead to different conclusions with respect to the variables of interest.[4]

Table 2 summarizes the results of the split-hazard model. In the logit part of our model, positive coefficients indicate a positive effect on the probability of eventual adoption, whereas in the hazard part, positive coefficients indicate a positive effect on the hazard rate. Consequently, variables with positive coefficients shorten the time to adoption. The estimation results reveal some significant effects of our included relationship characteristics in the logit part of the model, indicating that the nonadopters (or customers who resist the innovation) are indeed different from the adopters. The results also reveal significant effects of the considered marketing communications. We now discuss our results more specifically.

Marketing Communications

Direct marketing communications have a significant, positive effect on the hazard rate; these effects substantially shorten consumers' time to adoption. We also find a positive effect for service and brand advertising on adoption timing. When we test for the equality of the coefficients of service and brand advertising, we find that the effect of service advertising is significantly greater than that of brand advertising ($p < .01$). Therefore, H_1, H_2, H_3, and H_4 are all supported. In addition, our hypothesis about the market-making effect of competitive service advertising (H_5) is confirmed; we find a positive, significant effect on adoption timing. Finally, competitor brand advertising has a significant, negative effect, which implies that it lengthens the time to adoption, as H_6 predicts. Overall, the lagged effects of advertising expenditures are not significant, except for that of brand advertising.[5] The size of all mass advertising effects is considerably smaller than the size of the direct marketing communication effects (i.e., no increase in advertising expenditures can equal the effect of a direct marketing communication offer on individual hazard rates). However, the stronger direct marketing communication effect may be context dependent, as we discuss in our "Discussion and Implications" section.

Covariates

Relationship age has a significant (nonlinear) effect on adoption probability. Specifically, the probability of eventual adoption increases as the age of the customer's relationship with the provider increases, up to approximately three years. For customers who have been with the provider for more than three years, the adoption probability decreases. To some extent, this finding is in line with that of Reinartz and Kumar (2003), who report a nonlinear relationship between interpurchase times and lifetime duration. We do not find a significant effect of relationship age on adoption timing.

Service usage appears to be a significant indicator of both adoption probability and adoption timing. Customers with high usage levels are less likely to adopt the new service eventually than are customers with low usage levels. This effect might occur because customers with high usage levels are satisfied with the services they currently receive and thus have no need to adopt a new service. Given that

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[4] These estimation results are available from the first author on request.

[5] We also performed an additional analysis to assess further the potential long-term effects of the included marketing communications; specifically, using Nerlove and Arrow's (1962) approach, we considered the cumulative effects of advertising expenditures for all four types of marketing communications. Our estimation results did not reveal any cumulative effects for the focal supplier's service and brand advertising or for competitors' service advertising. We found an unexpected positive effect of cumulative competitive brand advertising. Given the absence of strong support for cumulative advertising effects, we do not report these effects.

TABLE 2
Estimation Results

	Logit Part: P(Adoption)		Hazard Part: Time to Adoption	
	Coefficient	z Value	Coefficient	z Value
t	N.A.		.1618	11.49***
t^2	N.A.		–.0048	–9.82***
Direct marketing communication	N.A.		1.8652	43.20***
Service advertising	N.A.		.2243	7.22***
Service advertising (t – 1)	N.A.		.0012	.05
Brand advertising	N.A.		.0521	2.25**
Brand advertising (t – 1)	N.A.		.0432	1.88*
Competitive service advertising	N.A.		.0969	4.85***
Competitive service advertising (t – 1)	N.A.		–.0065	–.29
Competitive brand advertising	N.A.		–.0863	–10.26***
Competitive brand advertising (t – 1)	N.A.		–.0078	–.85
Relationship age	.8493	1.75*	.0521	1.00
Relationship age^2	–.1296	–1.86*	–.0033	–.42
Service usage	–.2164	–3.00***	.0580	4.45***
Service usage^2	.0032	2.35**	–.0009	–2.45**
Age	–1.6270	–.88	–.2123	–1.55
Age^2	.2413	.97	–.0075	–.46
Gender	.4401	.62	–.1486	–2.44**
Domain-specific innovativeness	–.2685	–.44	.3166	2.84***
Constant	5.5730	1.67*	–3.6189	–11.98***
Log-likelihood	–13,586.947			
Likelihood ratio test	$\chi^2(28) = 1935.99$***			
AIC statistic	27,229.89			
BIC statistic	27,401.83			

*$p < .10$ (two-sided).
**$p < .05$ (two-sided).
***$p < .01$ (two-sided).
Notes: N.A. = not applicable.

they adopt, customers with high usage levels turn out to be the fastest adopters. This positive relationship between service usage and adoption timing suggests that despite a low adoption probability, heavy users tend to adopt faster than light users.

Interaction Effects

In addition to our analyses of the main effects displayed in Table 2, we perform an analysis on any possible interaction effects between direct marketing communication and mass marketing communication and between marketing communications and relationship characteristics. We include all interaction terms simultaneously in the split-hazard model we used previously, which does not change the other coefficients significantly. Therefore, we report only the interaction effects and relevant main effects in Table 3. Adding the interaction effects to the model improves the total model fit significantly ($\chi^2(7) = 24.724$, $p < .001$); the AIC statistic also decreases from 27,229.89 to 27,219.17.

The first interaction effect we investigate is that between direct marketing communication and service and brand advertising. The results suggest a negative interaction effect between direct marketing communication and service advertising, which indicates that the combined effect of the two types of marketing efforts on adoption timing is less than the sum of the separate positive effects. The interaction effect between direct marketing communication and brand advertising is not significant. Therefore, we do not find evidence for communication synergies between direct marketing communication and brand advertising, as H_7 and H_8 predict.

The second interaction effect we examine is that between relationship age and all types of marketing communications. The results suggest that the influence of service advertising efforts, whether by the provider or its competitors, is greater for customers who have been with the provider for a longer time. We did not find any significant interaction effects between (competitive) brand advertising and relationship age or between direct marketing communication and relationship age.

Discussion and Implications

In this study, we investigate the effects of marketing communications on the individual adoption timing of a new e-service by existing customers of a large Dutch telecommunications provider. In doing so, we integrate the literature streams of new product adoption and customer management. This integration and our data—including customer adoption behavior, customer-specific marketing

TABLE 3
Estimation Results Interaction Effects

	Hazard Part: Time to Adoption	
	Coefficient	**z Value**
Direct marketing communication (DMC)	1.9558	16.44**
Service advertising (SA)	.1841	4.88**
Brand advertising (BA)	.0323	1.06
Competitive service advertising (CSA)	.0829	3.48**
Competitive brand advertising (CBA)	−.0819	−8.01**
Relationship age (RA)	−.0345	−.41
RA^2	.0038	.36
DMC × SA	−.1226	−1.97*
DMC × BA	.0424	.92
RA × DM	−.0202	−.43
RA × SA	.0742	2.89**
RA × BA	.0004	.02
RA × CSA	.0380	2.12*
RA × CBA	−.0059	−.71
Log-likelihood	−13,574.585	
Likelihood ratio test	$\chi^2(35) = 1960.71$**	
AIC statistic	27,219.17	
BIC statistic	27,434.09	

*$p < .05$ (two-sided).
**$p < .01$ (two-sided).

interventions, advertising expenditure data, customer relationship characteristics, and customer characteristics—enable us to contribute to both literature streams. Table 4 reports a summary of our hypothesis-testing results; we discuss our most important findings and contributions next.

First, we study both direct marketing communication and mass marketing communication. These mass marketing communications include both advertising that communicates the new e-service and brand advertising, and we also consider the impact of these two advertising types from competing suppliers. In support of prior customer management research findings, we find that direct marketing communication shortens adoption timing (Verhoef, Franses, and Hoekstra 2001). This is an important extension of the knowledge pertaining to the possible effects of direct marketing communication. For example, it influences not only cross-buying of existing services but also the purchase of newly introduced services. The finding of an effect of direct marketing communication is also important for the adoption literature because so far, adoption researchers have ignored the impact of this type of communication on individual adoption behavior. Our study results emphasize the importance of direct marketing communication in influencing existing-customer adoption behavior. Consistent with previous adoption studies and diffusion research, we find a positive effect of the focal supplier's mass advertising expenditures on individual customers' adoption speeds. However, the effect on adoption timing is remarkably smaller than the effect of direct marketing communication. This could be because in this particular setting, mass communications, due to their focus on creating awareness and information provision, do not influence adoption behavior strongly. To affect behavior, more action-oriented communications, such as direct marketing communication, are required. However, this stronger effect of direct marketing communication may also be because we study the adoption behavior of existing customers, who might be more responsive to individually targeted marketing efforts. Furthermore, this result may be context dependent because we could investigate only one type of direct marketing communication and we did not have any influence on the content of the message. For example, it might have been possible for the provider to adjust the message to the individual customer's situation. Moreover, the strong effect of direct marketing communication might also be due to the firm doing a good job of selecting customers to contact by telephone. However, we controlled for this by including several covariates. Overall, we cannot draw any generalizable conclusions from the relatively strong direct marketing communication effect compared with the effect of mass marketing communications. Further research might aim to replicate our findings.

Second, this is the first study to distinguish explicitly between brand advertising and service advertising. We show that the effects of each type of mass advertising on individual adoption timing are notably different. Mass advertising that is specifically related to the new service has a greater effect on the time to adoption than does general mass advertising for the service provider's brand. This is not an unexpected finding, because service advertising has a more specific focus on the new service. Through service advertising, service providers mainly build consumer

TABLE 4
Summary of Hypothesis Testing Results

Variable	Hypothesis	Hypothesized Effect on Adoption Timing^a	Finding	Conclusion
Direct marketing communication (DMC)	H_1	+	+	Supported
Service advertising	H_2, H_4	+	+	Supported
Brand advertising	H_3, H_4	+	+	Supported
Competitive service advertising	H_5	+	+	Supported
Competitive brand advertising	H_6	−	−	Supported
DMC × service advertising	H_7	+	−	Not supported
DMC × brand advertising	H_8	+	n.s.	Not supported

^{a}Positive effects indicate a shorter time to adoption.
Notes: n.s. = not significant.

awareness and interest with respect to the new service category. However, the positive effect of general brand advertising on adoption behavior is remarkable. On the basis of general advertising theories, we argue that brand advertising positively affects attitude toward the brand, which in turn positively affects adoption behavior. However, there is still much that is unknown about this effect. For example, do improved brand perceptions positively affect adoption behavior? In this study, we did not account for intervening brand attitudes (or service attitudes). It would be worthwhile to include these attitudes in more extended models in further research. As we noted, customer management research has ignored mass advertising for several reasons. Our study shows that mass communications indeed affect adoption behavior of existing customers. This is an important finding, though it might be due to the specific nature of the behavior; namely, existing customers also need to be informed about the new service, which suggests a more important role of mass advertising. However, it may also point to a too narrow view of customer management researchers, who assume that after acquisition, existing customers focus mainly on the relationship itself and are no longer affected by mass advertising efforts. In general, the important role of advertising is acknowledged in frequently consumed packaged goods, for which advertising elasticities are found to be between 0 and .2 (Assmus, Farley, and Lehmann 1984; Vakratas and Ambler 1999). In these markets, advertising is required to reinforce the brand position continuously in the consumers' minds to affect buying behavior and, thus, brand loyalty in the store. The question is whether advertising also affects existing customers' behaviors, such as customer retention or cross-buying, in long-term (contractual) relationships. Our study may indeed point to the existence of these effects. However, further research should empirically establish whether these effects are actually present.

Third, our results show that competitive advertising efforts that feature similar services can accelerate the adoption process for first movers as well, which suggests that through service advertising, service providers mainly build consumer awareness and interest with respect to the new service category. It also confirms the market-making effect, which has been shown to be relevant at the aggregate diffusion level (e.g., Krishnan, Bass, and Kumar 2000). Our study is the first to show this effect at the individual adoption level. Our results also show that competitive brand advertising lengthens adoption timing. This finding is notable because it shows that even the adoption of new services by existing customers is affected by competitive actions that are not related to the specific new service. Theoretically, we reasoned that this effect might exist because of the effects of competitive advertising on brand attitudes of both the focal supplier and the competitor. However, we have no empirical evidence for this link, because we do not observe brand attitudes. More research is required here. The inclusion of competitive mass communication efforts is new for the customer management research literature. Most researchers have ignored the impact of competitive actions, though such actions are acknowledged to be relevant (e.g., Keiningham, Purkins-Munn, and Evans 2003). Our results emphasize the importance of these competitive actions. A next step in customer management research would be for researchers to include more competitive variables in their models.

Fourth, we examined various possible interaction effects in our analysis. Although we expected a positive synergy between direct marketing and mass marketing efforts, we find some rather less straightforward effects, including an unexpected negative interaction between service advertising and direct marketing communication. Prior research has also identified some negative interaction effects. Naik, Raman, and Winer (2005) argue that the price-oriented nature of promotions may reduce the effectiveness of advertising in building brands. Conversely, advertising may lower consumer sensitivity to promotions. Narayanan, Desiraju, and Chintagunta (2004) report a negative interaction effect between detailing and advertising in pharmaceutical markets. Bass and colleagues' (2005) reasoning is that there might be a kind of overkill. The advertising combined with direct marketing communication may result in too much attention for the new service, resulting in a negative interaction effect. Overall, additional research is required to understand these negative interaction effects, which are found more commonly in empirical research. We cannot find any significant interactions between brand advertising and direct marketing communication, which implies that there is no synergy between these marketing variables.

The interaction effects between marketing efforts and relationship age provide more intuitive results. Service advertising has a greater impact on more loyal customers, and the positive interaction effect between competitive service advertising and relationship age implies that the market-making effect does not work well for relatively new customers. Overall, the interaction effects between relationship age and marketing efforts provide further evidence that customers' heterogeneous responses to marketing efforts may be explained, at least partially, by relationship characteristics, such as relationship age (Rust and Verhoef 2005).

Fifth, from a modeling perspective, our research shows that it is important to account for the notion that certain customers will probably never adopt the new service. This supports the theoretical notion of innovation resistance mentioned in the adoption literature. So far, most adoption researchers do not account for this in their econometric model (e.g., Steenkamp and Gielens 2003). Thus, our study is one of the few studies to use a split-hazard model that accounts for this effect at the individual adoption level. However, we should mention that our model might also work well because of the limited time frame of the data. Usually, the takeoff of a new product or service may take several years (Tellis, Stremersch, and Yin 2003). Thus, we do not observe adoption for a large part of the existing customers included in our study; our model might consider such customers nonadopters, but they might adopt the product several years from now. However, recent adoption figures pertaining to the studied new service still show a limited number of adopters (see also Figure 2), indicating that innovation resistance might indeed be a problem. Notably, the split-hazard model may also have other applications in customer management research. For example, when modeling relationship duration, it might be assumed that there is a group of customers who are unlikely to churn (e.g., because of high switching costs) and that there is another group of customers who are at risk for churning. The latter group might be receptive to service improvement efforts, whereas the former group is almost nonresponsive. So far, researchers have not acknowledged modeling relationship duration that accounts for the appearance of these two groups of customers (e.g., Bolton 1998).

Sixth, our study is the first to investigate customer adoption of new services using data from a customer database. These data offer some notable insights, especially with respect to the effects of behavioral relationship characteristics on customer adoption behavior. Customers who have been with the provider for two or three years have the highest probability to adopt the new e-service eventually. The lower adoption probability for new customers may be explained by the contractual setting; these customers are still locked in to their recently established contract with the provider, and upgrading to a contract that includes the new service would be costly. The low adoption probability of customers who have been with the provider for a long time could be explained by customer life-cycle effects, such that in the later stages of the customer life cycle, customers are not likely to adopt new products or services. Customers with high usage levels, who are assumed to have a deeper relationship with the provider, are less likely to adopt the new service, which seems counterintuitive. However, customers with high usage levels who adopt indicate a relatively short time to adoption. Furthermore, we find that domain-specific innovativeness does not affect the probability of eventual adoption, but it shortens the time to adoption. A note of caution is required here because our measure for domain-specific innovativeness might be imperfect. Further research might, for example, use perceptual innovativeness measures instead of our behavioral indicator.

Management Implications

Speeding up the adoption of newly introduced services is important to many firms. This especially holds in the telecommunications industry, in which services are linked to large network technology investments. A successful introduction of these new services is required to get return on these investments. Existing customers are an important target group in the introduction of new services. However, the question is which marketing communications the firm should use to speed up adoption. Our results indicate that firms can use both direct marketing communication and mass marketing communication to shorten adoption timing. However, the effect of direct marketing communication is much larger than the effect of mass marketing communication. Thus, our results seem to suggest that speeding up adoption timing among existing customers should mainly be done with direct marketing communication. The role of mass marketing communication is only limited. However, mass marketing communication may still be required to reach noncustomers as well. Conversely, a strategy might be to focus on existing customers first to create a sufficiently large customer base to spread the new technology into the market further. This might point to potential cost savings for firms if they first use relatively cheap and more effective direct marketing communications and then use the existing customer base to create network effects.

Our results also show the importance of competitive advertising effects on the new service. Thus, a useful strategy might involve two or more competitors that simultaneously introduce a new service; this approach should accelerate the adoption process for every player in the market.

The results of our study, particularly the exploratory analyses of the interaction effects between marketing efforts and relationship age, reveal a significant role of customer loyalty in existing customers' adoption process. We find that loyal customers adopt sooner than relatively new customers and have a better response to mass marketing efforts. Therefore, building customer loyalty is important not only for customer retention and cross-selling but also for the adoption of new and additional services.

Research Limitations and Further Research

Our study has several limitations that suggest possible directions for further research. First, we consider only one service introduction in the telecommunications industry for a specific company. The question is whether our findings are generalizable to other contexts as well. This specific industry, company, and service have specific characteristics (e.g., a high degree of technological turbulence, high involvement, one of the larger market players). For example, in markets with lower-involvement products, the effects of mass advertising are likely to be smaller. Further research is required to study the effect of marketing communications on adoption behavior. Studying other industries and services would make it possible to study which market and service characteristics moderate the effects of marketing communications.

Second, we focus on the adoption behavior of existing customers only. Accordingly, our findings apply to this group alone. However, a considerable number of adopters were not customers of the provider before they adopted the new service. These customer acquisitions as a result of the introduction of the new service were not observed by the provider before the adoption, so we did not account for them. It would be worthwhile to investigate the specific effects of marketing communications on the adoption behavior of this specific group of consumers.

Third, we do not have any data about prices, income levels, or customer attitudes. Prices will most likely have a considerable impact on customers' adoption timing, but such data typically are difficult to retrieve in a mobile service context. Including customer attitudes in the model, such as customer satisfaction and the perceived usefulness of the new service, would also be a possible extension that could provide new and valuable insights into individual adoption behavior (e.g., Meuter et al. 2005).

Fourth, our results are limited to the communication types and content this provider used. For example, the direct marketing communication efforts consisted of telephone calls from the provider to existing customers. The found effects might be different if other instruments or content were used. Therefore, we cannot generalize our findings on the relative size of the effects of direct marketing communication and mass marketing communication on adoption timing. Further research might consider how instruments and content moderate the effect of marketing communications on adoption behavior.

Finally, we defined individual adoption as a dichotomous event—that is, the first trial of a new service. Continuous usage of the new service may be a better characterization of the adoption decision because some adopters could cease to use the service after the first trial. Therefore, a promising direction for further research would be to investigate postadoption usage and disadoption of new services in a customer management context.

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Xianjun Geng, Ruhai Wu, & Andrew B. Whinston

Profiting from Partial Allowance of Ticket Resale

For a seller that markets event tickets both in advance and on spot, a concern is that ticket resale may hurt its profitability. The conventional wisdom is for the seller to consider completely banning resale if possible. This article considers an alternative strategy in which resale is only partially restricted; specifically, resale is banned on spot but still allowed in advance. Using a two-period model in which buyers have discreet valuations, the authors show that it is possible for partial resale to outperform no resale (and also unrestricted resale at the other extreme) in terms of seller profitability when the following conditions hold: when the seller has limited capacity, when the number of high-valuation buyers is small enough, and when the number of early arrivers is not too large. An implication of this research is that when consumers conduct advance and spot resale in different channels, such as advance resale online and spot resale offline, the seller may be better off adopting different resale policies for different channels.

In recent years, the $200 billion event-ticket industry has witnessed a boom in ticket resale facilitated by online consumer-to-consumer markets (Townley 2002). For example, eBay now offers a major trading category called "Tickets and Experiences," in which consumers exchange a large amount of event tickets everyday with unprecedented reach and convenience.[1] Often, tickets sold in resale markets compete with those sold by initial ticket sellers (hereinafter, "sellers") and thus may affect seller profits.

This article examines the impact of resale on a ticket seller's profit using a two-period model. In this model, the seller offers some tickets at one posted price in the first period (called the "advance" period) and the rest at another, potentially different posted price in the second period (called the "spot" period). Some buyers ("early arrivers") arrive early enough in the market so that they have the option to buy tickets from the seller in either period, and the rest ("late arrivers") arrive late so that they can catch only the seller's spot selling. This two-period model, including the terminologies "advance" and "spot," is widely adopted in the academic literature on ticket resale and advance selling (Courty 2003a, b; Karp and Perloff 2005; Lee and Whang 2002; Rudi, Kapur, and Pyke 2001; Xie and Shugan 2001). The spot period usually has a short duration and is close to the event time (thus, the term "spot"); in contrast, the advance period lasts much longer.

This two-period model also fits a wide range of pricing practices in the event-ticket industry. For example, consider the box office at the University of Texas at Austin (UT). If a concert is scheduled for an evening, at the earliest, spot selling starts at noon on the same day at the concert hall until all tickets are sold out or until the concert begins, and advance selling starts two months ahead of this event day until advance tickets are sold out or until the spot selling starts. There is a similar practice at UT for sporting events. Such practices also take place in many other universities and colleges across the country. Off campuses, movie theater chains, and entertainment event organizers sell tickets weeks or months in advance online (e.g., fandango.com, ticketmaster.com) and also at the gate on the event day.

Resale among ticket buyers may take place either within the advance period, which we call "advance resale," or within the spot period, which we call "spot resale." Two widely applicable observations regarding advance and spot resale are worth mentioning. First, although the online channel (e.g., eBay) fits advance resale well, it is often not suitable for spot resale because of tight time constraints. In the UT example, there are fewer than eight hours between when the seller starts spot selling and when the concert begins, and the duration of an auction on eBay needs to be at least a whole day, not to mention the time needed for setting up an auction, negotiating payment method, receiving payment, and delivering the ticket. Therefore, spot resale

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[1] The term "ticket," as it is used in the ticket resale literature, refers to an option to consume a single-time consumption good at a fixed consumption time (also called the event time) (Happel and Jennings 2002). Therefore, the category includes more than tickets to entertainment or sports events; for example, a conference registration proof is also a form of ticket. Research on ticket resale is part of the larger literature on ticket selling (for an extensive review, see Courty 2000).

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still relies heavily on the traditional physical channel—namely, locations near event venues. Second, unlike online resale, which is allowed (sometimes with caps on resale prices) throughout the United States, resale at physical event venues is widely prohibited; it is banned at the state level in 23 states. Moreover, in states in which there is no state-level law against ticket resale, city-level or private ordinances often prohibit resale at event venues.[2] At UT, for example, resale is not allowed on campus. As a result, UT ticket holders in the spot period have no suitable channel to resell their tickets, though in the advance period, the online channel is a good choice.

We call the scenario in which advance resale is feasible but spot resale is infeasible "partial allowance of resale," or "partial resale" for short. These two observations imply that partial resale captures the characteristics of resale activities for a wide range of event tickets, in which the spot period is too short for online transactions and resale at event venues is prohibited.[3] Nevertheless, partial resale has received little academic attention. Prior research on ticket resale has not made a distinction between advance and spot resale (cf. Courty 2003b) and thus has concentrated on either complete resale (both advance and spot resale are feasible) or no resale (both are infeasible).

The prospect of partial resale raises several new research questions. What is a seller's optimal pricing strategy under partial resale? Can partial resale be more beneficial for the seller than complete and no resale, and if so, under what conditions? What are the implications of partial resale with respect to consumer surplus and social welfare? This article offers some answers to these questions.

There are three possible pricing strategies for the seller: "spot-only selling," in which no ticket is made available in the advance period; "discount advance selling," in which the seller's advance price is lower than the spot price; and "premium advance selling," in which the advance price is higher than the spot price.[4] We find that under partial resale, the seller adopts either spot-only selling or premium advance selling but not discount advance selling, which provides early arrivers a risk-free arbitrage opportunity in resale. Moreover, the seller may adopt premium advance selling only if it strategically rations the ticket supply in its advance selling and if its capacity is less than total buyer demand (hereinafter, we refer to this as the "limited-capacity" condition). Intuitively, an early arriver can buy from the seller's advance selling or can strategically wait and later buy from either a reseller or the seller in spot selling. Such a consumer will buy a premium-priced advance ticket from the seller only when he or she expects that tickets will be undersupplied in both the advance-resale market (because of rationing) and the spot period (because of limited capacity).

In a comparison, under complete resale, the seller always adopts spot-only selling, and under no resale, all three pricing strategies are possible.[5] Intuitively, any two-period selling strategy with different advance and spot prices is effectively a price discrimination mechanism. Complete resale, which provides an unconstrained environment for arbitrage, negates the seller's price discrimination attempt, and as a result, the seller cannot get a higher profit by two-period selling than by spot-only selling.

As the centerpiece of this article, we show that when the seller has limited capacity, when the number of high-valuation buyers is small enough, and when the number of early arrivers is not too large, the seller can get more profit under partial resale than under either complete or no resale. The first two conditions (limited capacity and a small enough number of high-valuation buyers) ensure that the seller will adopt premium advance selling under partial resale.

The third condition (that the number of early arrivers is not too large) is related to an important insight in our model; namely, partial resale offers the seller a new price discrimination mechanism that is unavailable under either complete or no resale. Recall that under complete resale, there is no price discrimination. Moreover, under no resale and premium advance selling, early buyers pay more than late buyers; in other words, early buyers are discriminated regardless of their valuations. In contrast, under partial resale, we show that all or most high-valuation buyers are discriminated because they pay the same high price regardless of when they arrive. This is because high-valuation buyers who arrive late must pay a premium to secure a ticket in the resale market. The third condition posits that the seller will prefer partial resale over no resale if discriminating high-valuation buyers are more profitable than discriminating early buyers.

Partial resale also has important implications for consumer surplus and social welfare. Compared with no resale, whenever partial resale gives the seller a higher profit, it also leads to equal or higher consumer surplus and social welfare. Intuitively, the resale of tickets from low-valuation buyers to high-valuation buyers strictly increases social welfare, whereas the improvement is shared by both buyers and the seller if premium advance selling is the seller's optimal strategy.

Our research adds to the small but growing literature on ticket resale.[6] The literature cites several factors that favor resale from a monopolistic seller's perspective. Deserpa (1994) and Swofford (1999) argue that uncertainty about buyer demand and risk aversion prompt the seller to take the safe route of underpricing, thus opening up the opportunity for resale.[7] Rudi, Kapur, and Pyke (2001) and Lee and Whang (2002) assume that the seller can sell only in the advance period and, thus, does not need to worry about demand reduction in the spot period when resale is feasible. Courty (2003a) assumes *ex ante* buyer valuation heterogeneity ("die-hard fans" and "busy professionals") and shows that resale enables the seller to capture value from both types of buyers. Williams (1994), Swofford (1999), and Karp and Perloff (2005) argue that resellers have an *ex ante* information advantage over the seller in terms of screening late buyers; thus, by allowing resale, the seller can capitalize on the efficiency gain when many tickets are sold at high prices (through resellers) to high-valuation buyers. Our research differs from these studies in that we focus on the value of partial resale to the seller, which none of this other research discusses. As our observations and results indicate, partial resale not only exists in practice but also may give the seller a higher profit than both complete and no resale.

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[2] For online resale, see eBay's information regarding regulations at http://pages.ebay.com/buyselltickets/rules.html; for resale at event venues, see the National Conference of State Legislatures' Web site at http://www.ncsl.org/programs/lis/ticketscalplaws.htm.

[3] Partial resale can also be implemented in a more explicit way, such that the seller issues anonymous tickets in an early stage and then requires them to be converted later into named ones. In practice, there may be buyers who are willing to take the risk to resell even if the law prohibits resale. As long as their resale volume accounts for only a negligible portion of the total sales by the seller, it does not affect our results qualitatively.

[4] Strictly speaking, the seller can also pick two other pricing strategies. One is when the advance and spot prices are the same; this pricing strategy always gives the seller the same profit as that under spot-only selling, regardless of resale activities. The other is advance-only selling, in which there is no spot selling; advance-only selling can be considered a special case of discount advance selling in which the spot price is very high.

[5] As we pointed out in n. 4, the seller can also adopt advance selling, in which advance and spot prices are the same.

[6] There is also an active literature on durable goods resale (see, e.g., Hendel and Lizzeri 1999). The overwhelming focus in

To our knowledge, the only other study that addresses the issue of partial resale is that of Courty (2003b); yet Courty argues that partial resale is never beneficial to the seller. A key difference between our model and Courty's is that we assume an exogenously given capacity constraint, whereas Courty does not. It turns out that capacity constraint is critical in determining the value of partial resale to the seller.

Our research is also related to the advance-selling literature, which, as with the literature on ticket resale, often uses the two-period posted-price model (Dana 1998; Shugan and Xie 2000; Xie and Shugan 2001). Specifically, our model is closely related to that of Xie and Shugan (2001) in that both models consider *ex ante* homogeneous buyers with both advance and spot arrivals. The advance-selling literature does not consider resale. In contrast, our article addresses the intertemporal resale activities among buyers that are popularly observed in online exchanges, such as eBay, and it shows that these resale activities may enable the seller to get a profit that is higher than that under no resale.

We begin by laying out the model in the next section. We then study the seller's optimal pricing strategy under partial resale. Next, we compare partial resale with complete and no resale and derive the conditions under which the seller gets more profit under partial resale. We also address the impact of partial resale on consumer surplus. We conclude by discussing the managerial implications and the limitations of our research.

The Model

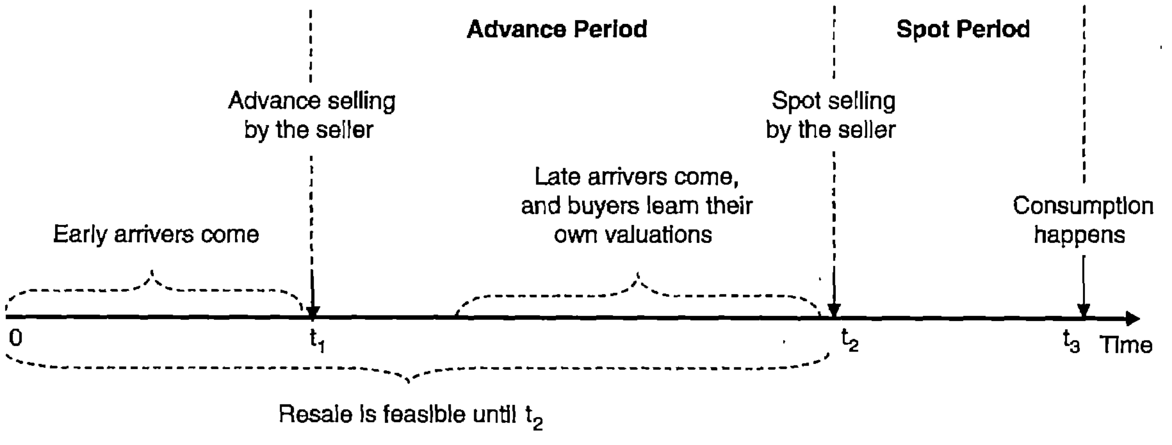
We develop a game-theoretical model for analyzing the impact of partial resale on seller profit. Let there be one monopolistic ticket seller and Ω buyers, each demanding one ticket at most.

The Seller

The seller's marginal cost for producing tickets is a constant normalized to zero. It has a capacity of $\hat{T}$ tickets. If $\hat{T} < \Omega$, the seller has a limited capacity. If $\hat{T} \geq \Omega$, the seller has an abundant capacity. Because there is no demand for any capacity beyond Ω, for simplicity and without loss of generality, we define $T = \min\{\hat{T}, \Omega\}$ and use T, instead of $\hat{T}$, in our analysis. Then, $\hat{T} \geq \Omega$ is equivalent to $T = \Omega$.

The seller uses a two-period posted-price selling strategy (for the model time line, see Figure 1). At the start of

FIGURE 1
The Model Time Line


Advance Period
Spot Period
Advance selling by the seller
Spot selling by the seller
Late arrivers come, and buyers learn their own valuations
Early arrivers come
Consumption happens
0
t_1
t_2
t_3
Time
Resale is feasible until t_2

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durable goods resale, which does not apply to tickets that can be consumed only once, is on the cannibalization effect of used goods on new goods.

[7] There are some other explanations for underpricing, such as protecting fairness and fostering loyalty, that benefit the seller in repeated interactions (for an overview, see Courty 2003a). Because we do not consider repeated interactions, these explanations are out of the scope of this article.

the advance period, t_1, the seller announces the advance price, p_1, and makes S_1 tickets available for advance selling, where $0 \le S_1 \le T$. The advance period lasts until the spot period starts at t_2. At t_2, the seller announces the spot price, p_2, and makes the rest of the tickets available for spot selling.[8] The spot period lasts until the event (consumption) time, t_3 ($t_3 > t_2 > t_1 > 0$). The advance period is usually much longer than the spot period in practice (often months versus days or even hours). Thus, we assume that $(t_2 - t_1) >> (t_3 - t_2)$. The seller is free to sell in either period or both. For the former case, the seller can simply make zero tickets available during one period.

Buyers

A buyer's ticket valuation can be one of two positive values, H or L, where $H > L > 0$.[9] Let there be $q\Omega$ buyers with valuation H and the rest with valuation L. We consider a case in which there is neither *ex ante* buyer valuation heterogeneity nor *ex ante* information asymmetry. In other words, *ex ante*, all buyers and the seller know the value of q, but none of the buyers knows his or her own valuation. Note that if $q \ge T/\Omega$, resale has no impact on the seller's profit; the seller can simply adopt spot-only selling at price H and get an optimal profit of TH regardless of resale activities. In this article, we focus on the more interesting case in which $q < T/\Omega$.

In this model, even if a buyer is capable of purchasing at a given moment, he or she might choose to wait if he or she expects a better deal later. Therefore, it is worthwhile to distinguish between a buyer's arrival and his or her actual purchase. We define a buyer's arrival time as the earliest time at which he or she is capable of buying. A buyer can then buy at any time from his or her arrival time to the event time. Let buyers be differentiated by their arrival times. Suppose that $\alpha\Omega$ buyers (among which $q\alpha\Omega$ have high valuations), or early arrivers, arrive before or at t_1 so that they can catch the seller's advance selling if they want ($0 < \alpha < 1$). The remaining $(1 - \alpha)\Omega$ buyers, or late arrivers, arrive after t_1 but before t_2 so that they can catch the seller's spot selling. Because $(t_2 - t_1) >> (t_3 - t_2)$, if buyer arrivals are smooth, the majority will arrive before or at t_2. In light of this, we ignore buyers who arrive after the start of the spot period. If an early arriver buys a ticket at p_1 from the seller, we call this person an early buyer.

Although *ex ante* a buyer is uncertain about his or her valuation of a ticket, he or she will resolve this uncertainty at a later time, such as when his or her schedule is finalized. We stipulate that each buyer's uncertainty resolves at a random moment within the advance period, that is, after t_1 and before t_2. In practice, some buyers may figure out their valuation early (before t_1) or late (after t_2), but as long as the number of these buyers is small, it does not qualitatively affect our results.

Partial Resale

Partial resale is the scenario in which advance resale is feasible but spot resale is infeasible. In other words, resale among buyers is feasible before t_2 (though before t_1, there is no resale activity, because there is no ticket available) and is infeasible from t_2 onward. Partial resale captures the characteristics of resale activities for a wide range of event tickets, such as the UT example, in which the spot period is too short for online transactions and resale at event venues is prohibited. Because a transaction cost–based argument is not the focus of this article, we assume that advance resale is perfect if it is feasible.[10]

For comparison purposes, we also subsequently discuss two alternative resale scenarios. One is complete resale, in which resale is feasible throughout the whole time line, and the other is no resale, in which resale is infeasible throughout the whole time line. As we mentioned previously, complete and no resale are the focus of prior research, and to date, partial resale has received little academic attention (cf. Courty 2003b).

In what follows, we study partial resale in two steps. First, we characterize the seller's pricing strategy and profit under partial resale in the next section. Second, we compare partial resale with complete and no resale.

Pricing Strategy Under Partial Resale

The seller has four possible pricing strategies: spot-only selling, in which $S_1 = 0$; discount advance selling, in which $S_1 > 0$ and $p_1 < p_2$; premium advance selling, in which $S_1 > 0$ and $p_1 > p_2$; and equal-price advance selling, in which $S_1 > 0$ and $p_1 = p_2$. Because equal-price advance selling always gives the seller the same profit as spot-only selling regardless of resale activities (for a proof, see Lemma 2 in the Appendix), for succinctness, we assume that if advance selling cannot give the seller a higher profit than spot-only selling, the seller will opt for spot-only selling. Thus, our analysis focuses on the first three pricing strategies. The following proposition characterizes the seller's optimal pricing strategy under partial resale:

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[8] The seller is free to announce p_2 well before offering the second round of tickets. However, buyers will not necessarily believe the announced price if the seller can later change it for the seller's own benefit. This is called "the credibility issue," and it is widely studied in marketing, economics, and finance. The credibility issue is consistent with the notion that in the ticket market, individual buyers have little power to monitor or enforce a monopolistic seller's preclaimed prices (Karp and Perloff 2004; Xie and Shugan 2001). Buyers trust the announced p_2 only from the start of the spot period, when tickets are indeed rolled out at this price.

[9] Strictly speaking, it is the valuation of the associated service provided to the ticket holder.

[10] A perfect resale market is one in which matching between buyers and sellers is costless and efficient in the sense that no Pareto improvement is possible any other way. To the best of our knowledge, the notion of a perfect resale market first appears in the work of Fox (1957).

P_1: Under partial resale, if

(a) $$q \ge \frac{T}{\Omega}\frac{L}{H} + \frac{1}{1/\min\{q,\ \alpha\}-1}\left(1-\frac{T}{\Omega}\right)\left(1-\frac{L}{H}\right),$$

the seller adopts spot-only selling with $p_2^* = H$, and the seller's profit is $q\Omega H$.

(b) $$q < \frac{T}{\Omega}\frac{L}{H} + \frac{1}{1/\min\{q,\ \alpha\}-1}\left(1-\frac{T}{\Omega}\right)\left(1-\frac{L}{H}\right)$$

and the seller has an abundant capacity (i.e., $T = \Omega$), the seller adopts spot-only selling with $p_2^* = L$, and the seller's profit is TL.

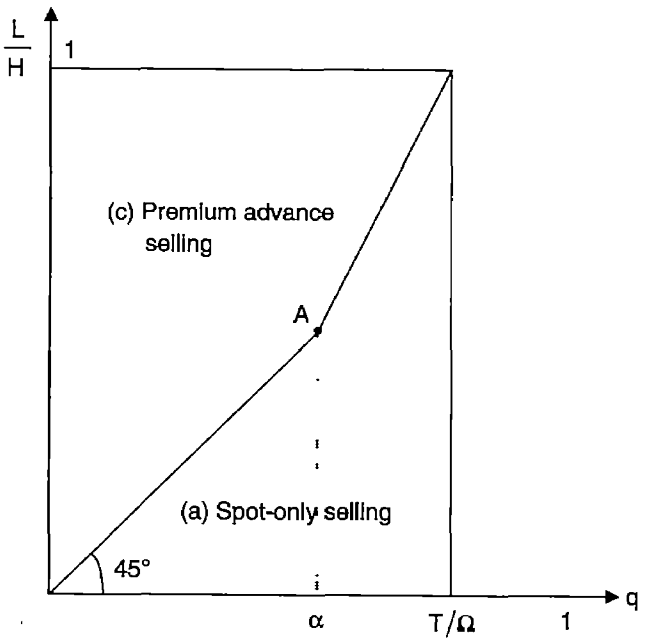
(c) $$q < \frac{T}{\Omega}\frac{L}{H} + \frac{1}{1/\min\{q,\ \alpha\}-1}\left(1-\frac{T}{\Omega}\right)\left(1-\frac{L}{H}\right)$$

and the seller has a limited capacity (i.e., $T < \Omega$), the seller adopts premium advance selling with $p_2^* = L$, $p_1^* = L + [(1 - T/\Omega)/(1 - \min\{q,\ \alpha\})](H - L)$, and $S_1^* = \min\{q,\ \alpha\}\Omega$. Moreover, all resellers in advance resale charge the same price as p_1^*. The seller's profit is $TL + (1/[1/\min\{q,\ \alpha\} - 1])(\Omega - T)(H - L)$.

For proofs, see the Appendix. Figure 2 helps illustrate P_{1a} and P_{1c} when $T < \Omega$. Again, we consider only $q < T/\Omega$ because under $q \ge T/\Omega$, the seller always adopts spot-only selling at price H. Moreover, because of the nonsmooth function $\min\{q,\ \alpha\}$, there is a kink (Point A) on the border of a and c. This kink exists only when $\alpha < T/\Omega$.

P_1 has several important implications. First, under partial resale, the seller may adopt premium advance selling but not discount advance selling. From the seller's perspective, a drawback of discount advance selling, in which $p_1 < p_2 = H$, is that it provides early buyers with a risk-free arbitrage opportunity that eventually takes away some of the seller's spot demand; when some early buyers find out that their valuation is L, they will resell their tickets to high-valuation late arrivers, which in turn reduces the seller's expected demand at its spot selling. Conversely, premium advance selling does not cannibalize the seller's spot demand; because $p_2^* = L$, all buyers without a ticket will try to purchase in the seller's spot selling, and tickets changing hands among buyers in advance resale does not reduce the number of buyers without tickets.

FIGURE 2
Optimal Pricing Strategy Under Partial Resale



This result of premium, but not discount, advance selling under partial resale is supported by anecdotal evidence. For any concert at UT, buyers always pay more when they purchase tickets online or by telephone well in advance than when they purchase tickets in person on spot. For example, an advance ticket for one recent concert cost $41.25, whereas a spot ticket cost $32.50. This price difference was due to "convenience and handling fees" totaling $8.75 (a quarter of the ticket's value) that are imposed when tickets are purchased online or by telephone. The UT box office acknowledged that online sales actually reduce costs because transaction automation reduces staff workload. Lacking a cost-based reason, the UT box office insists that these fees are just "standard to the industry." Premium advance selling is also frequently observed off campus, such as at many movie theater chains that charge more for purchasing online in advance than at the gate. In addition, higher advance prices often show up as other indirect fees. For example, fans often need to join an online club and pay a "club membership fee" to secure advance tickets. No such membership is needed if customers buy on spot (Ordonez 2003).

Second, P_{1c} captures two important conditions for the seller to adopt premium advance selling: The proportion of high-valuation buyers is small enough, and the seller has a limited capacity.[11] The first condition implies that the high-valuation market segment is not "juicy" enough for the seller to give up the low-valuation market segment altogether. As a result, the seller will use a low spot price, $p_2^* = L$, to capture the low-valuation demand.

The second condition (limited capacity) explains why the seller can get early buyers to pay a premium to purchase in advance, even when they expect a low spot price down the time line. If an early arriver waits instead of buys in the advance period, in the spot selling, he or she has a chance of $(\Omega - T)/(\Omega - S_1^*)$ not to get a ticket because of limited capacity, and thus the buyer suffers a net surplus loss of H if he or she turns out to be a high-valuation buyer. The premium of p_1^* over p_2^*, which is $([1 - T/\Omega]/[1 - \min\{q,\ \alpha\}])(H - L)$, can be viewed as an insurance premium that an early buyer is willing to pay to secure a ticket.

Limited capacity is frequently observed in the event-ticket industry. One reason is that seating capacity is often a long-term decision that is made well before total market demand (Ω) is known for any given event. In the UT example, almost all university-sponsored concerts use the same concert hall, regardless of the demand. Moreover, many entertainment venues offer significant discounts if a seller is able to make a long-term commitment. For example, an annual figure skating show, Champions on Ice (see www.championsonice.com), signed multiyear deals to use Everett Events Center as the show venue in western Washington. This show has since experienced exploding demand, but its commitment to use Everett Events Center prevents it from switching to another, larger arena to accommodate the growing demand.

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[11] The first condition, $q < ([T/\Omega][L/H]) + (1/[1/\min\{q,\ \alpha\} - 1])(1 - [T/\Omega])(1 - [L/H])$, can be rewritten as the following so that q does not appear on the right side: $q < (L/H)$ if $q \le \alpha$ and $q < ([T/\Omega][L/H]) + (1/[1/(\alpha - 1)])(1 - [T/\Omega])(1 - [L/H])$ if $q > \alpha$.

Third, in addition to limited capacity, which is an exogenously given condition, it is important for the seller to ration ticket supply endogenously by setting $S_1 \leq q\Omega$ in the advance period to induce purchase at the premium advance price. To understand this, suppose that the seller instead sets $S_1 > q\Omega$, and early arrivers still buy. Then, after all buyers arrive and they all learn their own valuations, in the advance-resale market, there will be fewer high-valuation buyers without a ticket than there are tickets available. Competition among resellers will then drive resale price down to L. Anticipating this, early arrivers will wait for resale and thus refuse to buy the seller's premium-priced advance tickets, which contradicts the assumption that early arrivers buy. In summary, early buyers pay a premium to buy in advance because they anticipate that tickets will be undersupplied in both the advance-resale market (because of rationing) and the spot period (because of limited capacity).

Fourth, partial resale is critical in determining the seller's advance price. Without advance resale, an early buyer is stuck with his or her ticket, and thus willingness to pay at the seller's advance selling is, at most, his or her expected valuation, $L + q(H - L)$. With advance resale, nevertheless, a buyer has the option to resell when his or her valuation turns out to be L. As a result, case P_{1c} shows that the seller can now charge $p_1^* = L + ([1 - T/\Omega]/[1 - \min\{q, \alpha\}])(H - L)$, which can be higher than a buyer's expected valuation when q is small enough. This last implication of P_1 will be useful when we compare the seller's profits under the three resale scenarios in the next section.

A Comparison of Partial, Complete, and No Resale

In this section, we answer the question whether and when partial resale is more beneficial for the seller than the other two resale scenarios (i.e., complete and no resale). In preparation, we first derive the seller's pricing strategy under both complete and no resale. Similar to our analysis under partial resale, for complete and no resale, we also assume that if advance selling (premium or discount) cannot give the seller a profit higher than spot-only selling, the seller will opt for the latter. Moreover, we keep the assumption that $q < T/\Omega$ because, otherwise, the seller always adopts spot-only selling with price H and always gets a profit of TH regardless of resale scenarios.

P_2: When spot resale is feasible (as under complete resale), if

(a) $$q \geq \frac{T}{\Omega}\frac{L}{H},$$

the seller adopts spot-only selling with $p_2^* = H$, and the seller's profit is $q\Omega H$.

(b) $$q < \frac{T}{\Omega}\frac{L}{H},$$

the seller adopts spot-only selling with $p_2^* = L$, and the seller's profit is TL.

Under complete resale, high-valuation buyers have the option to wait until the last minute to buy from low-valuation resellers through the spot-resale market. P_2 shows that this option for buyers makes it impossible for the seller to do any better than spot-only selling. Intuitively, unconstrained arbitrage opportunity negates the seller's attempt to price discriminate by means of advance selling.

Corollary 1: The case in which spot resale is feasible (as under complete resale) always leads to a profit for the seller that is lower than or equal to the one under the case in which spot resale is not feasible (as under partial or no resale).

Corollary 1 follows from the notion that under partial or no resale, the seller can always choose spot-only selling, which results in a profit that is the same as that under complete resale. Because complete resale is always the worst among the three resale scenarios for the seller in terms of profit, hereinafter we focus on partial and no resale in our comparison. Note that Corollary 1 is consistent with our previous observation that resale at physical event venues (in which spot resale can take place) is widely prohibited by state and city laws and private ordinances.

P_3: Under no resale, if

(a) $$q > \frac{T/\Omega - \alpha}{1 - \alpha},$$

the seller adopts discount advance selling with $p_2^* = H$, $p_1^* = L + q(H - L)$, and $S_1^* = (T - q\Omega)/(1 - q)$, and the seller's profit is $TL + q\Omega(H - L)$.

(b) $$\frac{T/\Omega - \alpha}{1 - \alpha} \geq q \geq \frac{T/\Omega - \alpha}{1 - \alpha} \times \frac{L}{H},$$

the seller adopts discount advance selling with $p_2^* = H$, $p_1^* = L + q(H - L)$, and $S_1^* = \alpha\Omega$, and the seller's profit is $q\Omega H + (1 - q)\alpha\Omega L$.

(c) $$q < \frac{T/\Omega - \alpha}{1 - \alpha} \times \frac{L}{H}$$

and the seller has an abundant capacity, the seller adopts spot-only selling with $p_2^* = L$, and the seller's profit is TL.

(d) $$q < \frac{T/\Omega - \alpha}{1 - \alpha} \times \frac{L}{H}$$

and the seller has a limited capacity, the seller adopts premium advance selling with $p_2^* = L$, $p_1^* = L + ([1 - T/\Omega]/[1 - \alpha])(H - L)$, and $S_1^* = \alpha\Omega$, and the seller's profit is $TL + q(\alpha/[1 - \alpha])(\Omega - T)(H - L)$.

P_{3b}–P_{3d} exist if and only if $\alpha < T/\Omega$. This proposition is a generalization of Theorem 7 in the work of Xie and Shugan

(2001). In their model, half the buyers arrive for advance selling. In our model, any arbitrary portion of buyers, α, may arrive for advance selling. This distinction is important because in P_4, we show that the value of partial resale to the seller depends on α. Figure 3 illustrates this proposition under limited capacity, where areas a, b, and d represent P_{3a}, P_{3b}, and P_{3d}. We are now in a position to answer the question whether and when partial resale is more beneficial for the seller than no resale.

P_4: If $q < \frac{T/\Omega - \alpha}{1 - \alpha} \times \frac{L}{H}$

and the seller has a limited capacity (i.e., $T < \Omega$), the seller always adopts premium advance selling under either partial resale or no resale. Moreover, the seller gets a higher profit under partial resale than under no resale if $\alpha < 1/(2 - q)$.

P_4 corresponds to Area I in Figure 4, which exists if and only if $\alpha < T/\Omega$. As a key contribution of this article, this proposition shows that it is possible for partial resale to be more beneficial to the seller than both complete and no resale. In other words, spot resale does not benefit the seller (as in P_2), but advance resale might. Consequently, it is possible for a seller to be resistant to spot resale and, at the same time, to accommodate advance resale. This result is consistent with our prior observation that, in practice, advance resale often receives less stringent restrictions by laws and private ordinances than does spot resale.

The first two conditions in P_4 (i.e., when the number of high-valuation buyers is small enough and when there is a limited capacity) ensure that the seller will adopt premium advance selling; the former leads the seller to price low in the spot period to cater to the low-valuation demand, and the latter explains why early arrivers buy premium-priced advance tickets rather than wait.

FIGURE 3
Optimal Pricing Strategy Under No Resale

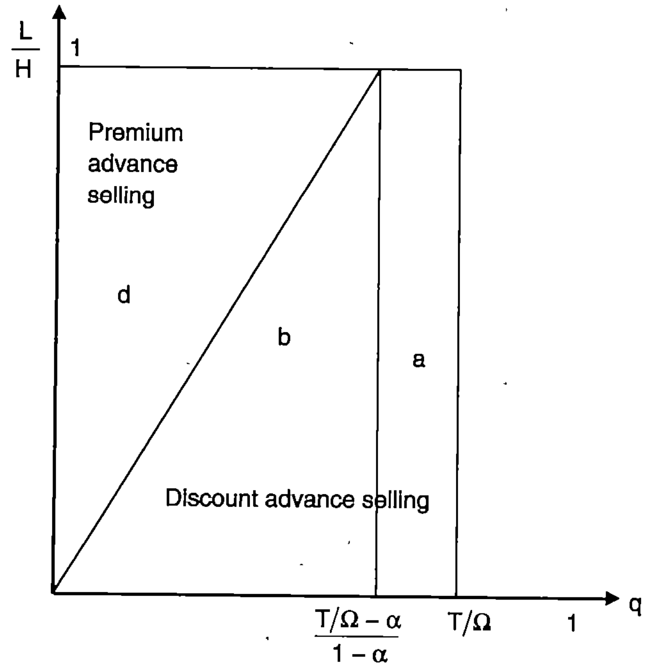
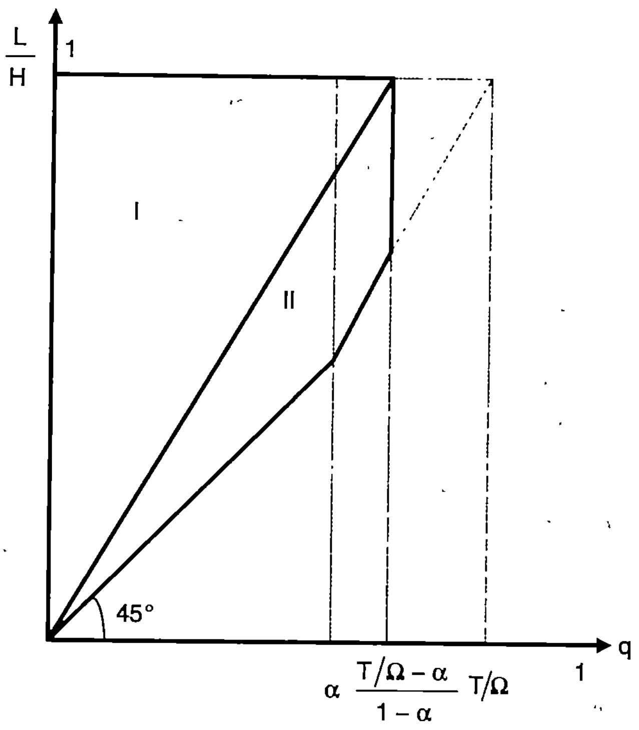


FIGURE 4
A Comparison of Partial and No Resale



When the two conditions hold, P_4 posits that partial resale benefits the seller more than no resale (and complete resale as in Corollary 1) when a third condition (i.e., the number of early arrivers is not too large) holds. To understand the implication of this condition, consider the following corollary:

Corollary 2: Given partial resale and that the seller adopts premium advance selling, if $q \leq \alpha$, all high-valuation buyers pay a same price of $L + ([1 - T/\Omega]/[1 - q])(H - L)$, regardless of their arrival time.

Corollary 2 directly follows P_1. It reveals an important insight in our model; namely, partial resale offers the seller a new price discrimination mechanism that is unavailable under either complete or no resale. Under partial resale and if $q \leq \alpha$, all high-valuation buyers will pay the same high price no matter when they arrive. Intuitively, because of limited capacity and ticket rationing, a late high-valuation buyer will try to secure a ticket in the advance-resale market, in which resellers, who are low-valuation ticket holders, will charge an insurance premium. Anticipating the premium in advance resale, the seller will also charge a premium in its advance selling. The seller's premium is the same as the premium in advance resale because, in equilibrium, the seller squeezes all expected surplus from early buyers. Consequently, early high-valuation buyers must pay the same premium as in advance resale.

If $q > \alpha$, this new price discrimination mechanism still works but only on some high-valuation buyers—specifically, on all early high-valuation buyers and $(1 - q)\alpha\Omega$ late high-valuation buyers. This is because in advance selling, the seller cannot sell more tickets than total market demand at that time. At most, there are only $\alpha\Omega$ tickets in the advance period, but in advance resale, there will be $q\Omega$ high-valuation buyers. Thus, some of these high-valuation buyers must wait for the seller's spot selling, for which the price is L.

In contrast to the case of partial resale, with no resale, early and late high-valuation buyers pay different prices if the seller adopts premium or discount advance selling. Partial resale is more beneficial to the seller than no resale if discriminating high-valuation buyers are more profitable than discriminating early buyers, which is when the number of early arrivers is not too large; in turn, this is the condition that $\alpha < 1/(2 - q)$ in P_4 implies.[12]

Note that $\alpha < 1/(2 - q)$ is not a very restrictive requirement on α. For example, any $\alpha \leq 1/2$ satisfies this requirement. In other words, if a seller adopts premium advance selling under both partial and no resale and if the majority of buyers arrive late, partial resale always gives the seller a higher profit than no resale.

It is worthwhile to point out that P_4 depends on our model assumption that, *ex ante*, an early arriver is equally likely to be of high-valuation as a late arriver.[13] In practice, however, it is sometimes possible that high-valuation buyers have a tendency to arrive early (Courty 2003a), in which case partial resale can be less beneficial to the seller than P_4 posits. The intuition is clear in the extreme case in which all high-valuation buyers arrive early: There is no point for the seller to use advance resale to capture surplus from late high-valuation arrivers, because there is no such buyer.

Thus far, we have assumed that the resale scenario—whether it is partial, complete, or no resale—is exogenously given. In practice, however, it is sometimes possible for a ticket seller to pick between different resale scenarios. When introducing the UT example, we mentioned that online advance resale is active; implicit in this example is that all UT concert tickets are anonymous. The UT box office could switch to named and nontransferable tickets and could check whether ticket and personal identifications match at the event gate (as airlines do). By doing so, the UT box office could change the resale scenario from partial to no resale. The next corollary provides managerial guidelines when the resale scenario is an endogenous decision variable for the seller.

> Corollary 3: Suppose that the seller can pick among resale scenarios at no cost. If under no resale the seller's optimal pricing strategy is premium advance selling, it should switch to partial resale if $\alpha < 1/(2 - q)$.

Corollary 3 directly follows from P_3 and P_4. As a special case of Corollary 3, if the seller's optimal pricing strategy under no resale is premium advance selling and if the majority of buyers arrive late ($\alpha \leq 1/2$), the seller should switch to partial resale for a higher profit.

Alternatively, if the seller's optimal pricing strategy under no resale is discount advance selling, it might intuitively be construed that it never pays for the seller to switch to partial resale, because under discount advance selling, partial resale provides early buyers with a risk-free arbitrage opportunity that eventually takes away some of the seller's spot demand. However, this intuition is incorrect, as P_5 shows.

> P_5: $$\text{If } \frac{T/\Omega - \alpha}{1-\alpha} \times \frac{L}{H} \leq q \leq \min\left\{\frac{L}{H}, \frac{T/\Omega - \alpha}{1-\alpha} \times \frac{L}{H} + \frac{\alpha(1 - T/\Omega)}{1-\alpha}, \frac{T/\Omega - \alpha}{1-\alpha}\right\}$$
>
> and the seller has a limited capacity (i.e., $T < \Omega$), the seller adopts premium advance selling under partial resale and discount advance selling under no resale. Moreover, the seller gets a higher profit under partial resale than under no resale if $TL + (1/[1/\min\{q, \alpha\} - 1])(\Omega - T)(H - L) > q\Omega H + (1 - q)\alpha\Omega L$.

P_5 corresponds to Area II in Figure 4, which exists if and only if $\alpha < T/\Omega$. Even for a seller that adopts discount advance selling under no resale, it may still pay for it to switch to partial resale. Key to this result is the notion that when the seller changes the resale scenario from no to partial resale, in equilibrium, the seller also needs to adjust its pricing strategy accordingly because discount advance selling is no longer optimal. Consequently, the seller switches to premium advance selling, and advance resale will not reduce the seller's spot demand.

Because of the simultaneous change of resale scenario and pricing strategy, we cannot give simple criteria for when partial resale benefits the seller more than no resale. Nevertheless, for any set of given parameters, the seller can simply compute the profits under both resale scenarios and then select the best one.

For example, let $\alpha = q = .15$, $L/H = .36$, and $t/\Omega = .5$. This set of parameters satisfies the conditions in P_5. Therefore, under no resale, the seller adopts discount advance selling, which leads to a profit of $.1959\Omega H$. Under partial resale, the seller adopts premium advance selling, which leads to a profit of $.2365\Omega H$. By switching from no resale to partial resale, the seller's profit increases by 20.7%.

Consumer Surplus

The previous section establishes that partial resale can be more beneficial to the seller than no resale. In this section, we show that partial resale can be more beneficial than no resale to buyers as well.

> P_6: Compared with no resale, whenever partial resale gives the seller a higher profit, consumer surplus is the same when
> $$\alpha \leq q \leq \frac{T/\Omega - \alpha}{1-\alpha} \times \frac{L}{H},$$
> and it is strictly higher otherwise.

P_6 shows that partial resale can be a win–win choice for both the seller and the buyers. Whenever partial resale is a better resale scenario for the seller than no resale, consumer surplus is never hurt, and in some cases, it is possibly higher (e.g., when $q < \alpha$). Intuitively, the price that early buyers pay is strictly higher than L under either premium or discount advance selling under both partial and no resale.

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[12] Alternatively, $\alpha < 1/(2 - q)$ can be rewritten as $q > 2 - 1/\alpha$, which implies that partial resale is better than no resale when the number of high-valuation buyers is not too small.

[13] We thank an anonymous reviewer for this comment.

Under no resale, early buyers are stuck with their ticket; thus, a buyer with a low valuation ends up paying more than what the ticket is worth. Under partial resale, however, such buyers can resell the ticket to high-valuation buyers to avoid a net loss. The flow of tickets from low- to high-valuation buyers leads to a more efficient resource allocation among buyers, and the efficiency gain can be shared by both the seller and the buyers, as P_6 shows.

Managerial Implications

The conventional wisdom is to take a holistic view of a resale market; that is, it is either entirely good or entirely bad for a monopolistic ticket seller in terms of profitability. Reflecting this, the overwhelming majority of research on ticket resale considers only two options: either to ban resale completely or to allow resale completely. Nevertheless, such a view is increasingly at odds with recent developments in the event-ticket industry and resale markets. A prominent development is the emergence of the Internet and the subsequent adoption of multichannel (online and physical) selling strategies by both sellers and consumers. As we noted previously, buyers increasingly use the online channel for resale in advance, but they still rely heavily on the physical channel for resale on spot. Therefore, a resale market can at least be divided into the online part (advance resale) and the physical part (spot resale).

We found that spot resale is always detrimental to a seller's profit because it offers a last-minute arbitrage opportunity for buyers, which in turn defeats the seller's attempt to price discriminate. Therefore, sellers should consider prohibiting spot resale whenever possible. This finding is consistent with our observation that spot resale at physical venues is widely banned across the United States.

In the rest of the article, we assume that spot resale is always prohibited. This leaves us with two resale scenarios: partial resale, in which advance resale is allowed and spot resale is prohibited, and no resale, in which both advance and spot resale are prohibited. In the UT example, the former implies banning physical resale yet allowing online resale, and the latter implies banning resale in both channels. A comparison of partial resale and no resale reveals an important insight into their distinctive impacts on a seller's price discrimination practice. `Partial resale enables the seller to discriminate all or most high-valuation buyers, regardless of their arrival time. In contrast, no resale enables the seller to discriminate buyers on the basis of their arrival time. Therefore, when advance price is higher than spot price, the seller should compare the profits it can get by discriminating high-valuation buyers and by discriminating early buyers. If the former is larger than the latter, the seller should adopt partial resale.

For a seller that adopts partial resale, our research offers several pricing suggestions. First, to induce early arrivers to buy in advance directly from the seller rather than to wait for the resale market, the seller should ration ticket supply in the advance period to create supply scarcity in the advance-resale market. Second, the seller should set an advance price higher than the spot price. Otherwise, the advance-resale market offers early buyers an arbitrage opportunity because they can buy low and sell high, which reduces the seller's spot demand. Finally, the advance price the seller sets under partial resale should be higher than the one under no resale because under partial resale, an early buyer has the option to resell his or her ticket, which in turn increases his or her willingness to pay.

Note that a seller's pricing strategy and resale policy are not isolated from each other; when the seller considers changing its resale policy, it may also need to adjust its pricing strategy accordingly. Specifically, we point out that for a seller that switches from no resale to partial resale, if it used to charge a lower advance price than the spot price, it should also switch to charging a higher advance price to fit the partial resale practice.

Although the focus of this research is on seller profitability, we also show that compared with no resale, partial resale never hurts and often increases consumer surplus. In other words, partial resale can be a win–win solution for both sellers and buyers.

Limitations and Further Research

As one of the first articles to explore partial resale, our study has several limitations that further research could address. First, the model we use assumes a discreet distribution of buyer valuations. Therefore, the impact of partial resale on seller profit under a continuous distribution of buyer valuations remains an open question. Second, this study considers only one specific way of dividing a resale market along time. A seller could potentially divide a resale market in other ways and could subsequently practice other forms of partial resale. Third, this study assumes a monopolistic seller; therefore, the results cannot be directly applied to sellers in competitive markets, such as airlines. That said, because partial resale can increase consumer surplus in the monopoly case, it would be worthwhile to study whether this result of increased consumer surplus can be extended to the competitive case, making partial resale not only a price discrimination tool but also a competitive advantage for a ticket seller.

We conclude by calling for caution when ticket sellers and policy makers contemplate using new technologies against new resale channels, such as the online channel. Technology advancements, such as electronic authentication and identification, digital rights management, and the prevalence of electronic payment, provide sellers with increasingly powerful tools to control resale in the online channel. Specifically, if a ticket seller has long prohibited spot resale (and has long benefited from the prohibition) by traditional means such as on-spot patrol or video surveillance, it may be tempting for it to consider taking advantage of newly available technologies and to extend resale prohibition to other channels, such as the online channel. As we observed, the online channel differs significantly from the physical spot channel because the former often fits advance resale better than spot resale; thus, resale activities online may actually benefit the seller even when physical spot resale does not.

Appendix

In preparation for the proof of P_1, we first prove Lemmas 1–5 in a backward order with respect to the time line. Let π_1

denote the seller's profit from advance selling, and let π_2 denote its profit from spot selling. Let M_1 denote the number of tickets traded in advance resale.

Lemma 1: In the spot period, if $(L/H) \leq ([q\Omega - qS_1 - M_1]/[T - S_1])$, then $p_2 = H$; otherwise, $p_2 = L$.

Proof. In the spot period, all buyers know their own valuations. The seller's spot selling is the last chance for buyers to purchase a ticket because spot resale is infeasible. Consequently, the seller will set its optimal price, p_2^*, at either H or L, depending on whether it wants to serve only high-valuation buyers or all buyers. If $p_2 = H$, then $\pi_2 = (q\Omega - qS_1 - M_1)H$. If $p_2 = L$, then $\pi_2 = (T - S_1)L$. This lemma follows a comparison of these two numbers.

Lemma 2: The seller cannot do better by equal-price advance selling than by spot-only selling.

Proof. Suppose in equilibrium that the seller sets $p_1 = p_2$ and that $S_1 > 0$. If $p_1 = p_2 = H$, no one buys at the seller's advance selling because $qH + (1 - q)L < p_1$, and resale price can never be higher than H. Thus, the seller is effectively practicing spot-only selling.

If $p_1 = p_2 = L$, all buyers will buy whenever possible. The seller's profit is TL, which is the same as that under spot-only selling with price L.

Lemma 3: All resale prices in advance resale are the same (denoted as p_{r1}).

Proof. If there are more low-valuation ticket resellers in advance resale than there are high-valuation buyers without a ticket, competition on the resellers' side will drive resale price down to the time-invariant price L.

Otherwise, we denote the negotiated price of the nth ticket resold in advance resale as $P_{r1}(n)$, where $1 \leq n \leq M_1$. For convenience, we call the reseller of the nth ticket the nth reseller. We want to show that $P_{r1}(n) = P_{r1}(M_1)$ holds true for any $n < M_1$. The term $P_{r1}(M_1)$ is the price of the last ticket resold in advance resale, and $P_{r1}(M_1)$ is determined such that a high-valuation buyer is indifferent about buying from the M_1th reseller or waiting for the monopolistic seller's spot selling.

If for some $n < M_1$ we have $P_{r1}(n) < P_{r1}(M_1)$, the best strategy for the nth reseller is to refuse to sell until the price is high because there are always high-valuation buyers without a ticket. However, if for some $n < M_1$ we have $P_{r1}(n) > P_{r1}(M_1)$, a high-valuation buyer without a ticket should refuse to buy because he or she will be better off waiting for the spot selling. Therefore, $P_{r1}(n) = P_{r1}(M_1)$ holds true for any $n < M_1$; thus, we can denote all resale prices in advance resale using a time-invariant variable, p_{r1}.

Lemma 4: If the seller adopts advance selling (either premium or discount), then $S_1 \leq q\Omega$, and $M_1 = (1 - q)S_1$. Moreover, if $(L/H) \leq ([q\Omega - S_1]/[T - S_1])$, then $p_{r1} = H$. Otherwise, $p_{r1} = L + ([\Omega - T]/[\Omega - S_1])(H - L)$.

Proof. We first show that $S_1 \leq q\Omega$. Assume, on the contrary, that the seller adopts advance selling and sets $S_1 > q\Omega$ in equilibrium. Then, $(1 - q)S_1 > q\Omega - qS_1$; that is, in advance resale, there are more low-valuation ticket holders than high-valuation buyers who have no tickets. Consequently, the equilibrium price in advance resale will be driven down to L because of competition among resellers. Because buyers expect enough tickets in the resale market at price L, they will refuse to pay more than L at the seller's advance selling. As a result, $p_1 = p_2 = L$, which contradicts the assumption that the seller adopts (premium or discount) advance selling.

Because $(1 - q)S_1 \leq q\Omega - qS_1$, a reseller will always be able to find a buyer if it offers a low enough price. Because advance resale provides a reseller with the only chance to resell, the buyer has the incentive to buy; thus, $M_1 = (1 - q)S_1$.

Resale price p_{r1} should make a buyer indifferent between buying from a reseller and buying from the seller's spot selling. When $(L/H) \leq ([q\Omega - S_1]/[T - S_1])$, then $p_2 = H$ (recall Lemma 1); thus, $p_{r1} = H$. When $(L/H) > ([q\Omega - S_1]/[T - S_1])$, then $p_2 = L$. Because all buyers will try to secure a ticket in the spot market, a high-valuation buyer has only a $(T - S_1)/(\Omega - S_1)$ chance to get one. From $H - p_{r1} \geq ([T - S_1]/[\Omega - S_1])(H - L)$, we have $p_{r1} = L + ([\Omega - T]/[\Omega - S_1])(H - L)$.

Lemma 5: If the seller adopts advance selling, its optimal advance price is $p_1 = p_{r1}$.

Proof. An early arriver's expected surplus from advance buying is $ESA = q(H - p_1) + (1 - q)(p_{r1} - p_1)$, and his or her expected surplus from waiting is $ESW = q(H - p_{r1})$. To induce early arrivers to buy, the seller must pick p_1 such that $ESA \geq ESW$. Therefore, to maximize its profit, the seller will pick p_1 such that $ESA = ESW$. We are now ready to prove P_1.

Proof of P_1

From Lemmas 1, 4, and 5, we have three alternatives:

1. If $(L/H) \leq ([q\Omega - S_1]/[T - S_1])$ holds, then $p_1 = p_{r1} = p_2 = H$, and the seller's total profit is $\pi = q\Omega H$. In this case, the seller can set $S_1 = 0$ and simply spot sell at price H.
2. If $(L/H) > ([q\Omega - S_1]/[T - S_1])$ holds and $T = \Omega$, then $p_1 = p_{r1} = p_2 = L$, and the seller's total profit is $\pi = TL$. In this case, the seller can set $S_1 = 0$ and simply spot sell at price L.
3. If $(L/H) > ([q\Omega - S_1]/[T - S_1])$ holds and $T < \Omega$, then $p_2 = L$, $p_1 = p_{r1} = L + ([\Omega - T]/[\Omega - S_1])(H - L)$, and the seller's total profit is $\pi = TL + (S_1/[\Omega - S_1])(\Omega - T)(H - L)$, which is an increasing function of S_1.

When $T = \Omega$ (abundant capacity), the seller picks between Alternatives 1 and 2 on the basis of which gives it the highest profit. This leads to P_{1b}. Now consider that $T < \Omega$, such that the seller picks between Alternatives 1 and 3. Recall from Lemma 4 that $S_1 \leq q\Omega$. Furthermore, the number of advance tickets sold cannot be greater than the number of early arrivers (i.e., $S_1 \leq \alpha\Omega$). Therefore, $S_1 \leq \min\{q, \alpha\}\Omega$.

When $q < (T/\Omega)(L/H) + (1/[1/\min\{q, \alpha\} - 1])(1 - [T/\Omega])(1 - [L/H])$ holds, $(L/H) > ([q\Omega - \min\{q, \alpha\}]/[T - \min\{q, \alpha\}])$. Therefore, in Alternative 3, the seller's profit is maximized at $S_1 = \min\{q, \alpha\}\Omega$, and the profit is $TL + (1/[1/\min\{q, \alpha\} - 1])(\Omega - T)(H - L)$. Then, $TL + (1/[1/\min\{q, \alpha\} - 1])(\Omega - T)(H - L) > q\Omega H$ can be rewritten as $q < (T/\Omega)(L/H) + (1/[1/\min\{q, \alpha\} - 1])(1 - [T/\Omega])(1 - [L/H])$.

Therefore, the seller will prefer Alternative 3 over Alternative 1. This is P_{1c}.

When $q \geq (T/\Omega)(L/H) + (1/[1/\min\{q, \alpha\} - 1])(1 - [T/\Omega])(1 - [L/H])$ holds, the profit in Alternative 3 is never higher than $q\Omega H$ for any $S_1 \leq \min\{q, \alpha\}\Omega$. Therefore, the seller prefers Alternative 1 over Alternative 3. This is P_{1a}.

Proof of P_2

The seller should set spot price p_2 only as H or L to maximize profit during spot selling. At any p_2 between H and L, the seller faces the same demand as at $p_2 = H$, but it gains less profit from each ticket.

P_{2a}. No low-valuation buyers will buy tickets from the seller in the spot period if $p_2 = H$, because resellers will set the resale price lower than H. If $S_1 > q\Omega$, there will be more resellers than high-valuation buyers in the spot period. The spot-resale price p_{r2} will converge to L, and no one will buy from the seller in the spot period. Furthermore, because high-valuation buyers will always get tickets at L from the resale market, they can only accept an advance selling price, p_1, that is no higher than L. Thus, the seller's total profit is $S_1(L - c)$, which is less than that from spot-only selling.

If $S_1 \leq q\Omega$, all low-valuation early buyers will resell their tickets to the high-valuation buyers in either the advance-resale market or the spot-resale market. Thus, in the spot period, the seller can sell no more than $q\Omega - S_1$ tickets as long as $p_2 > L$. Therefore, the seller's total profit is less than or equal to $q\Omega(H - c)$, which is the seller's profit without advance selling.

P_{2b}. All T tickets will be sold out if $p_2 = L$. Because $q\Omega < T$, all high-valuation buyers may purchase tickets from either the seller at $p_2 = L$ or the spot-resale market at $p_{r2} = L$. Therefore, the advance selling price p_1 can only be L. Thus, the seller's total profit is $T(L - c)$, which is less than or equal to its profit without advance selling.

Proof of P_3

We use backward induction in this proof. First, we assume that S_1 tickets are sold in advance selling at p_1 and consider the seller's spot selling. There are $\Omega - S_1$ consumers and $T - S_1$ tickets left on entering the spot selling. If the seller sets the spot price, p_2, at H, its spot profit is $\pi_2 = \min\{q(\Omega - S_1), (T - S_1)\}H$; if the seller sets the spot price at L, its spot selling profit is $\pi_2 = (T - S_1)L$. The seller will set the spot price to maximize its profit in spot selling; thus, the optimal outcome of the spot selling is as follows:

$$\begin{array}{lll}
\text{If } q \geq \dfrac{T - S_1}{\Omega - S_1}, & p_2^* = H & \pi_2 = (T - S_1)H \\[2ex]
\text{If } \dfrac{T - S_1}{\Omega - S_1} \geq q \geq \dfrac{T - S_1}{\Omega - S_1}\dfrac{L}{H}, & p_2^* = H & \pi_2 = q(W - S_1)H \\[2ex]
\text{If } q < \dfrac{T - S_1}{\Omega - S_1}\dfrac{L}{H}, & p_2^* = L & \pi_2 = (T - S_1)L
\end{array}$$

Second, we consider the seller's advance selling. Note that $S_1 \leq \min\{\alpha\Omega, T\}$. For ease of exposition, we denote $r = q/(L/H)$. Early arrivers will buy tickets in advance if and only if their expected surplus from advance purchase (ESA) is larger than or equal to their expected surplus from waiting (ESW). We consider the following three cases:

> Case 1: $q \geq ([T - S_1]/[\Omega - S_1])$, or equivalently $S_1 \geq ([T - q\Omega]/[1 - q])$.

In this case, the expected spot price is H, and we have $ESA = q(H - p_1) + (1 - q)(L - p_1) = qH + (1 - q)L - p_1$, and $ESW = 0$. Therefore, the seller's optimal advance price is $p_1^* = qH + (1 - q)L$, and its total profit from the two period sales is $\pi = S_1(qH + [1 - q]L) + \min\{q(\Omega - S_1), (T - S_1)\}H = TH - S_1(1 - q)(H - L)$. Because $\partial\pi/\partial S_1 < 0$, in Case 1, the seller would like to sell as few tickets as possible, subject to the constrains that $S_1 \leq \min\{\alpha\Omega, T\}$ and $S_1 \geq ([T - q\Omega]/[1 - q])$.

> Case 2: $([T - S_1]/[\Omega - S_1]) \geq q \geq ([T - S_1]/[\Omega - S_1])(L/H)$, or equivalently $([T - q\Omega]/[1 - q]) \geq S_1 \geq ([T - r\Omega]/[1 - r])$.

We still have the expected spot price being H, and thus $p_1^* = qH + (1 - q)L$. The seller's total profit from both periods is $\pi = S_1(qH + [1 - q]L) + \min\{q(\Omega - S_1), (T - S_1)\}H = q\Omega H + S_1(1 - q)L$. Because $\partial\pi/\partial S_1 > 0$, in Case 2, the seller would like to sell as many tickets as possible, subject to the constrains that $S_1 \leq \min\{\alpha\Omega, T\}$ and $([T - q\Omega]/[1 - q]) \geq S_1 \geq ([T - r\Omega]/[1 - r])$.

> Case 3: $q < ([T - S_1]/[\Omega - S_1])(L/H)$, or equivalently $S_1 < ([T - r\Omega]/[1 - r])$.

The expected spot price is L. Note that some consumers cannot get tickets in spot selling because of limited supply. As such, $ESA = qH + (1 - q)L - p_1$, and $ESW = q(H - L)([T - S_1]/[\Omega - S_1])$. Therefore, the seller's optimal advance price is $p_1^* = L + q(H - L)([\Omega - T]/[\Omega - S_1])$, and its total profit from both periods is $\pi = S_1(L + q[H - L][\{\Omega - T\}/\{\Omega - S_1\}]) + (T - S_1)L = S_1q(H - L)([\Omega - T]/[\Omega - S_1]) + TL$. Because $\partial\pi/\partial S_1 > 0$, in Case 3, the seller would like to sell as many tickets as possible, subject to the constrains that $S_1 \leq \min\{\alpha\Omega, T\}$ and $S_1 < ([T - r\Omega]/[1 - r])$.

We can now determine the seller's optimal choice of S_1 by comparing its highest profit in the foregoing three cases. If $q < ([T/\Omega - \alpha]/[1 - \alpha])(L/H)$, or equivalently $\alpha\Omega < ([T - r\Omega]/[1 - r])$, Cases 1 and 2 are impossible. Therefore, $p_2^* = L$, $S_1 = \min\{\alpha\Omega, T\} = \alpha\Omega$, $p_1^* = L + q([\Omega - T]/[\{1 - \alpha\}\Omega])(H - L)$, and seller profit is $TL + q(\alpha/[1 - \alpha])(\Omega - T)(H - L)$.

If $([T/\Omega - \alpha]/[1 - \alpha]) \geq q \geq ([T/\Omega - \alpha]/[1 - \alpha])(L/H)$, or equivalently $([T - r\Omega]/[1 - r]) \leq \alpha\Omega \leq ([T - q\Omega]/[1 - q])$, Case 1 is impossible. Note that we now have the following:

- In Case 2, $\max\limits_{S_1} \pi = \pi|_{S_1 = \alpha\Omega} = q\Omega H + (1 - q)\alpha\Omega L$.
- In Case 3, $\max\limits_{S_1} \pi = \pi|_{S_1 = \frac{T - r\Omega}{1 - r}} = q(T - r\Omega)(H - L) + TL$.

Straightforward algebra shows that under $([T - r\Omega]/[1 - r]) \leq \alpha\Omega \leq ([T - q\Omega]/[1 - q])$, $q\Omega H + (1 - q)\alpha\Omega L$ is larger than $q(T - r\Omega)(H - L) + TL$. Therefore, $p_2^* = H$, $S_1^* = \alpha\Omega$, $p_1^* = L + q(H - L)$, and seller profit is $q\Omega H + (1 - q)\alpha\Omega L$.

If $q > ([T/\Omega - \alpha]/[1 - \alpha])$, or equivalently $\alpha\Omega > ([T - q\Omega]/[1 - q])$, Cases 1 and 2 have the same optimal S_1 that equals $([T - q\Omega]/[1 - q])$. Note that

$$\max_{S_1}\{\pi|p_2^* = H\} = \pi|_{S_1 = \frac{T - q\Omega}{1 - q}} \geq \max_{S_1}\{\pi|p_2^* = L\} = \pi|_{S_1 = \alpha\Omega}.$$

Therefore, $p_2^* = H$, $p_1^* = L + q(H - L)$, $S_1^* = ([T - q\Omega]/[1 - q])$, and seller profit is $TL + q\Omega(H - L)$.

Proof of P_4 and P_5

To decide the seller's optimal choice on resale, we compare the profits shown in P_1 and P_3 for all possible overlapping situations. Because the seller always chooses spot selling if it has an abundant capacity, resale has no impact on its profit in this situation. Suppose that the seller has a limited capacity. We can pick any point in the q – (L/H) space and check which area it belongs to in Figures 2 and 3, compare the respective profits under partial resale and under no resale, and find the seller's optimal choice. For convenience, we use AI and AIII to represent cases a and c in P_1, respectively, and BI, BII, and BIV to represent cases a, b, and d in P_3, respectively. To simplify further, we write AX ≥ BY if we pick any point from the intersection of cases AX and BY (X = [I, III] and Y = [I, II, IV]) and find that seller profit on this point under partial resale is always higher than or equal to that under no resale. Similarly, there can be other inequalities between cases.

We now consider the overlapping area BIV and AIII. If $\alpha \leq q$, then $\pi_{AIII} = T(L - c) + (\alpha/[1 - \alpha])(\Omega - T)(H - L) > \pi_{BIV} = T(L - c) + q(\alpha/[1 - \alpha])(\Omega - T)(H - L)$, AIII ≥ BIV; if $q < \alpha \leq (1/[2 - q])$, then $\pi_{AIII} = T(L - c) + (q/[1 - q])(\Omega - T)(H - L) \geq \pi_{BIV} = T(L - c) + q(\alpha/[1 - \alpha])(\Omega - T)(H - L)$, AIII ≥ BIV; if $\alpha > (1/[2 - q])$, then AIII ≥ BIV. Thus, P_4 is proved.

Furthermore, BII may overlap with AI and AIII. P_3 proved that discount advance selling is more profitable than spot-only selling in case BII. Thus, BII > AI. If we compare the seller's profits in AIII and BII, there is no simple formula for determining which one is larger. The seller chooses partial resale and premium advance selling if $\pi_{AIII} = TL + (1/[1/\min\{q, \alpha\} - 1])(\Omega - T)(H - L) > \pi_{BII} = q\Omega H + (1 - q)\alpha\Omega L$. Thus, P_5 is proved.

Finally, BI may overlap with AI and AIII. In line with P_3, BI > AI. If $\alpha < q$, then $\pi_{AIII} = T(L - c) + (\alpha/[1 - \alpha])(\Omega - T)(H - L) < T(L - c) + (q/[1 - q])(\Omega - T)(H - L) < \pi_{BI} = T(L - c) + q\Omega(H - L)$, and thus BI > AIII; if $\alpha > q$, because $T/\Omega > q$, $\pi_{AIII} = T(L - c) + (q/[1 - q])(\Omega - T)(H - L) < \pi_{BI} = T(L - c) + q\Omega(H - L)$, and thus BI > AIII.

Proof of P_6

We use AI and AIII to represent cases a and c in P_1, respectively, and BI, BII, and BIV to represent cases a, b, and d in P_3, respectively.

In AI, consumer surplus is zero because the seller sells tickets at H only to high-valuation buyers. In AIII, consumer surplus is $CS_{AIII} = q\Omega(H - L)([T - \min\{q, \alpha\}\Omega]/[\Omega - \min\{q, \alpha\}\Omega])$.

In BI and BII, consumer surplus is also zero. Some early buyers may have high valuation at spot and will gain a surplus of $qS_1(H - [L + q\{H - L\}]) = q(1 - q)S_1(H - L)$, but the others have low valuation and will get a negative surplus of $(1 - q)S_1(-q[H - L]) = -q(1 - q)S_1(H - L)$. Therefore, the total surplus under discount advance selling is zero. In BIV, consumer surplus is $CS_{BIV} = q\Omega(H - L)([T - \alpha\Omega]/[\Omega - \alpha\Omega])$. As such, BIV overlaps with AIII. Thus, $CS_{BIV} < CS_{AIII}$ if $q < \alpha$, and $CS_{BIV} = CS_{AIII}$ if $\alpha \leq q$. P_6 follows the comparison of all overlapping areas.

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Katrijn Gielens & Marnik G. Dekimpe

The Entry Strategy of Retail Firms into Transition Economies

International entries into transition economies occur infrequently and involve considerable uncertainty. This raises the question whether managers, who have limited own experience, take their competitors' prior decisions into account when deciding on their own entry timing and size and whether there is value in doing so. To address these questions, the authors estimate a sequential hazard/Poisson regression model on the top 75 European grocery retailers' decisions to enter the Eastern European market. Indeed, firms pay close attention to prevailing practices in their industry. Prior entries first serve as legitimation but eventually become a deterring factor. Moreover, rather than just imitating the most popular or modal decision when determining the own entry timing and size, managers pay closer attention to the actions of their home competitors, react to prior entries of same-format competitors differently from those of different-format competitors, and adjust the observed industry practice for the specificity of their own resources. The authors show that managers are justified in taking the combined industry wisdom into account; deviations from prevailing industry practice, in terms of both timing and size, hurt the efficiency of their operations in subsequent years. Thus, attempts to develop own, distinct entry rules tend to be dysfunctional. Moreover, corrective actions are easier to implement along the size than along the time dimension; the detrimental effects of entering at a different time from the industry norm persist and even become amplified over time, whereas the negative impact of size deviations is temporary.

Cross-country capacity expansion is a fundamental option of strategic diversification, but it is still little understood (Martin, Swaminathan, and Mitchell 1998). On the one hand, many firms are reluctant to commit substantial resources to a new host market quickly, especially in light of the considerable uncertainty that often accompanies foreign-market entry and the realization that investments are largely sunk when initial expectations fail to materialize. On the other hand, firms in many industries tend to be confronted with a saturated market demand in their home country, and they often fear being left out of interesting growth opportunities abroad as a result of investing too little, too late. Because of this ambiguity, there is a wide variety of entry strategies, even within the same industry. Some players follow a cautious expansion strategy and enter late on a limited scale, and others try to establish a substantial presence as quickly as possible.

In this article, we provide a conceptual framework to understand the variability in firms' entry timing and size, and we argue that these decisions are influenced not only by the firm's own international experience (as Mitra and Golder [2002] demonstrate) but also by the internationalization activities a company observes with its competitors. Although it could be argued that markets with less direct competition are more attractive, firms may actually orient their own international expansion decisions toward the actions of or toward a subset of their competitors. Especially in the light of limited own experience and considerable demand uncertainty, firms may need to resort to inter- rather than intraorganizational learning to evaluate and legitimize alternative expansion options. If such interorganizational learning takes place, relevant questions become which competitors constitute the reference group, whether the presence of more competitors always offers a legitimization effect, and whether there is a critical number beyond which a deterrence effect dominates. These issues ultimately lead to the questions whether and to what extent it pays to adhere to "industry wisdom."

Using a sequential hazard/Poisson regression model, we test the proposed conceptual framework on a data set that covers all the top 75 European grocery retailers' decisions to expand into Central and Eastern Europe (CEE). The grocery retailing industry has only recently begun to explore the opportunities that foreign expansion offers. As recently as the early 1990s, foreign sales accounted for less than 5% of the turnover of the world's top retailers, thus lagging most of their suppliers. However, this pattern is rapidly changing. For example, the 15 leading international grocery retailers already realized more than 25% of their 2003 sales through their international operations (M+M Planet Retail 2005) and are known to grow faster abroad than domestically. Still, despite this growing international activity, many grocery retailers appear to be struggling to develop the competencies needed to compete and survive in this more global arena (Kumar 1997). Few succeed in obtaining com-

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parable margins and returns through their foreign operations compared with their home markets, and many do not break even. Some of these disappointing results have been attributed to the notion that retailers often appear to be motivated less by the chance of creating value in a new market than by the fear of being left out by their competitors (*The Economist* 1999), suggesting that interfirm imitation is indeed an issue.

Contribution

So far, the academic literature on foreign entry and expansion decisions has focused mostly on performance consequences. For example, Luo (1998) studies the short-term performance consequences of the timing, entry mode, and degree of diversification of foreign entries in the light industry, and Mascarenhas (1997) investigates the impact of entry size and order of entry in the oil rig market. In the retailing industry, Gielens and Dekimpe (2001) study the long-term performance consequences of standardization, mode, timing, and size of entry.

Another stream of literature focuses on which firm and market factors drive initial entry decisions. As such, questions about the extent to which rivals' actions are followed and imitated, the match between home- and host-market profile, and which firm characteristics tend to be associated with foreign entry become relevant. Answering these questions helps managers not only select entry strategies given the host-market situation and their own firm profile but also predict the type of competitors they are likely to face at the time of entry (Fuentelsaz, Gomez, and Polo 2002).

We extend this latter research stream in four ways. First, although recent research has considered the timing of foreign entry (Mitra and Golder 2002), the size decision has been largely ignored. Still, international entries can be considered "lumpy" investments of firm resources in an environment characterized by uncertainty about future performance, which necessitates attention to two key dimensions: when investments in foreign operations are made and how much resources are invested (Bar-Ilan and Strange 1999). Ayal and Zif (1979) argue that firms can choose between two expansion alternatives. To overcome resource and information constraints, they can act cautiously and postpone major investments. In contrast, to make sure not to forgo opportunities, firms may enter quickly and at full force. Both options have different timing and size implications. If retailers have different firm-specific resources and/or if managers differ in their interpretation of various market signals, the timing and extent of their entry may vary considerably. We develop a framework that helps explain this variability.

Second, we focus on the impact of interfirm learning from observing rival foreign activities. After controlling for the intraorganizational learning effects identified in prior research (Mitra and Golder 2002), we assess whether interorganizational learning has any further explanatory power. Moreover, in line with Debruyne and Reibstein's (2005) recent work, we argue that firms do not treat their competitive landscape as homogeneous but react more to some moves than to others. Firms may compose their competitive reference group in various ways, and we assess the impact of two reference schemes. First, we consider whether firms react differently to home than to foreign competitors. Second, we consider whether retailers with a similar store format constitute the reference group that is imitated or avoided.

Third, we reflect on the costs of deviating from industry practice. If competitive entry decisions are monitored closely, to what extent does it actually pay to adhere to this "combined industry wisdom"? Can managers turn to prevailing practices in the industry to learn which decisions are good or even best (Anderson 1988; Geletkanycz and Hambrick 1997)? We study whether firms whose entry timing and size conform to the pattern of decision making in the industry (as captured in our descriptive models) perform better than firms that deviate from these rules. Moreover, we evaluate whether these performance premiums are temporary or permanent and for which decision, timing or size, is adherence to industry practice more critical.

Fourth, we consider all entries made by the top 75 Western European grocery retailers in 11 CEE transition economies. Entries into these economies provide an ideal setting in which to assess potential imitation and competition effects. Transition economies constitute a major growth opportunity in today's world order (Arnold and Quelch 1998). They are also characterized by a substantial amount of environmental uncertainty, making organizational learning both more difficult and essential (Luo and Peng 1999). Moreover, all CEE markets opened up and became an investment opportunity to all retailers at the same time. However, instead of witnessing an undifferentiated rush into all these markets, entry patterns differed substantially across both retailers and host markets.

Research on emerging markets has been relatively neglected in the marketing literature. Still, "these countries represent the growth and future of [U.S.] companies" (Steenkamp 2005, p. 7), and there is increasing evidence that multinational corporations should rethink their traditionally deployed marketing strategies when dealing with emerging markets (Arnold and Quelch 1998); that is, they should not necessarily use their "developed-world" decision rules as a default option.

Conceptual Framework

In every entry-timing and -size decision, firms must consider market uncertainty and the potential irreversibility of investments (Ghemawat 1991). Because of the perceived opportunity costs or because firms do not want to commit themselves (yet) in the midst of high uncertainty, they may be reluctant to enter a specific market. Indeed, early and extensive commitments tend to reduce flexibility and increase risk exposure (Miller and Folta 2002). This applies to every foreign investment, but it is especially relevant in our setting. Export opportunities tend to be missing in the retail industry (Erramilli and Rao 1993). To reach potential customers, retailers must set up stores, which requires forging logistic networks, developing relationships with new suppliers, and managing assortments of thousands of products. This constitutes a considerable investment that is largely sunk after it is made. Moreover, there is considerable uncertainty on the demand side. Local consumer tastes may differ from those in the home country, and the concept of modern retail distribution tends to be unfamiliar in most emerging economies (Dries, Reardon, and Swinnen 2004). In addition, Western retailers initially did not have any experience operating in such markets, and the extent to which macroeconomic and institutional factors would change was unclear.

To explain the timing and size decision when firms enter transition economies, we consider how firms may obtain information about the attractiveness of these markets. Specifically, we study the extent to which the presence of other retailers may legitimize or deter entry. Apart from this interorganizational knowledge transfer, we also acknowledge the value of intrafirm knowledge derived from a given retailer's own experience in similar markets, and we control for other firm resources and various host-market characteristics (for a graphic representation of our conceptual framework, see Figure 1).

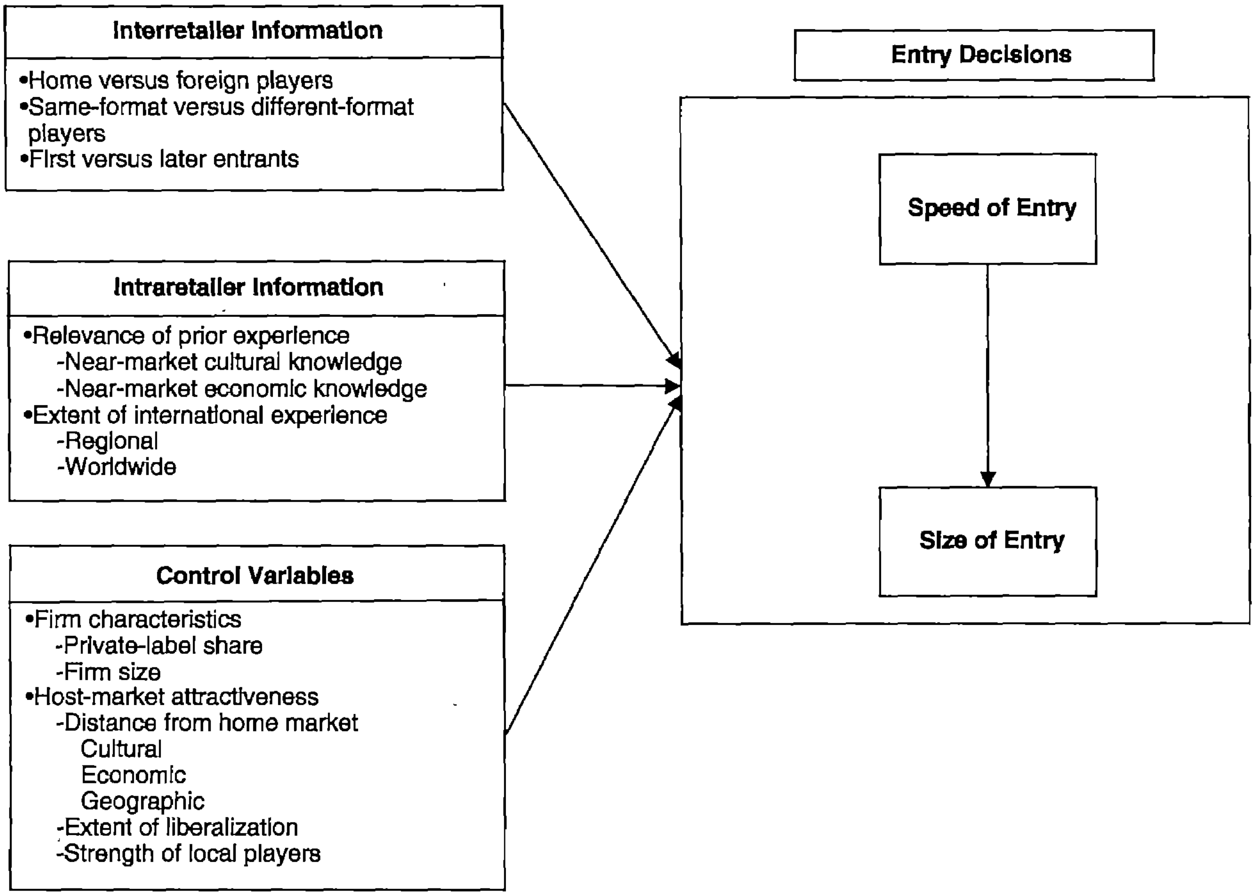
Interretailer Information

Lack of accurate information about the retail opportunities in a new market increases uncertainty and may delay entry (Martin, Swaminathan, and Mitchell 1998). However, prior decisions by other retailers may provide crucial information about the success potential of a foreign venture (see, e.g., Henisz and Delios 2001). Following what seems to be the industry norm reduces uncertainty and enhances legitimacy because a given practice is often viewed as appropriate. Thus, a firm's initial urge to remain cautious is expected to decrease when rival players enter the host market.

In contrast, other researchers have emphasized the view that rival players tend to decrease host-market opportunities. With every rival that enters, market competition becomes tougher, raising a barrier to further entry. Cotterill and Haller (1992) point out that especially in the context of grocery retailing, aggressive responses to subsequent entries are common.

The ecology literature (Hannan and Freeman 1977) reconciles both views, arguing that the presence of rivals initially facilitates a process of social recognition or legitimization and therefore attracts new entrants into the host market. Still, as competitive investments in the host country increase, the best geographical locations become preempted, and some interesting market opportunities become depleted, creating a deterring effect that eventually dominates the legitimization effect. Following this line of reasoning, we expect that there are two opposing forces at work: rival imitation and deterrence. Although these forces are not directly measurable, we use them to derive a testable hypothesis about the dependence between the entry rate in a

FIGURE 1
Conceptual Framework


Interretailer Information
•Home versus foreign players
•Same-format versus different-format players
•First versus later entrants
Intraretailer Information
•Relevance of prior experience
-Near-market cultural knowledge
-Near-market economic knowledge
•Extent of international experience
-Regional
-Worldwide
Control Variables
•Firm characteristics
-Private-label share
-Firm size
•Host-market attractiveness
-Distance from home market
Cultural
Economic
Geographic
-Extent of liberalization
-Strength of local players
Entry Decisions
Speed of Entry
Size of Entry

given country and its competitive density. This dependence has been found in many contexts to take the form of an inverted U shape (for an extensive review, see Carroll and Hannan 2000).

As is postulated in competitive cognition theory (e.g., Debruyne and Reibstein 2005), companies may not view their competitive landscape as homogeneous and thus may not attach equal weight to all potential competitors. As such, the relevant consideration set may not consist of all players in the industry but rather only those retailers with which they share some key attributes (Guillén 2002). We consider two kinds of commonalities that may drive how retailers perceive their competitive environment: (1) country of origin and (2) retail format.

The impact of home versus foreign rivals. Information about the expansion process and relative success of domestic rivals not only may be easier to obtain but also may be perceived as more relevant than information from other entrants. Because of their common background, observing how the home-market rivals operate in the new host market may be more effective in reducing uncertainty. Moreover, retailers may be more inclined to monitor their home rivals closely because they may fear the potential cross-subsidization toward the home market that might result from a successful international expansion (Flowers 1976).

The impact of same-format versus different-format retailers. Retailers may be influenced more by firms with a similar value proposition. Retail formats differ in terms of their assortment size and composition, their price and service level, and/or the overall perceived quality of their products (Kahn and McAlister 1997). On the one hand, the experience of rivals that operate a similar store format may be more informative than that of different-format retailers, resulting in a more pronounced legitimization effect. On the other hand, because same-format rivals tend to target the same customer segment in a comparable way, their presence may result in intense competitive retaliation and opportunity reduction, thus creating a strong deterrence effect.

Finally, we consider whether the first entrant of a given type (domestic or foreign, same format versus different format) creates a differential imitation effect. Other players may believe that the pioneer exploits information asymmetry and can capitalize on superior information to identify interesting market opportunities better or more quickly (Carow, Heron, and Saxton 2004; Lieberman and Montgomery 1988). Therefore, the pioneer's entry may give players a stronger signal about the potential of the market and may significantly reduce the perceived risks of also entering.

Intraretailer Information

Competitive actions may not be the only relevant source of information for the entry-timing and -size decision. Prior experience, especially in culturally and economically similar markets, may also be an important source of knowledge (Mitra and Golder 2002).

Extent of international experience. Experience has been shown to be a prime source of learning in organizations (Luo and Peng 1999). As firms gain experience in assessing prevailing business practices and consumer preferences in various host markets, the perceived risk of further international expansion is reduced. We distinguish between worldwide and regional experience. The former refers to a firm's global presence without reference to a specific market (Li 1994). Operating in many countries increases the variety of events to which a firm is exposed, which leads to a more extensive and diverse knowledge base. The latter is acquired through operations in a specific target area because such operations cause logistical and more extensive intelligence-gathering advantages in that region (Li 1994; Tan and Vertinsky 1996). Both forms of experience are believed to increase the speed and size of entry.

Relevance of prior experience. The more similar a potential host market is to other markets with which the firm already has experience, the easier is the transfer of knowledge. Following the work of Mitra and Golder (2002), we consider the impact of prior experience in both culturally and economically similar markets. The former, which is referred to as near-market cultural knowledge, reduces potential acculturation problems (Barkema, Bell, and Pennings 1996), whereas its economic counterpart helps replicate the firm's business in countries in which customer income and the cost and quality of resources are similar (Ghemawat 2001). Both forms of market knowledge are believed to impact the speed and size of entry positively.

Control Variables

To assess the impact of the aforementioned inter- and intrafirm information sources, we control for two firm-specific characteristics. We also control for the attractiveness of the host country.

Firm Characteristics

Assortment policy. Most retailers entering new (especially emerging) markets are unknown to their potential customers. Retailers that rely on private labels must convince customers in the new markets not only to switch stores but also to switch brands. Moreover, investments in private-label programs can be interpreted as a commitment to the home market, which reduces the number of resources available for foreign expansion. In terms of the branded products retailers want to carry in their foreign stores, they may also not have as comfortable a position in manufacturer–retailer negotiations as other retailers (Kumar 1997). Finally, private-label programs require the retailer to carry a lot of functions and costs normally taken care of by the manufacturer. Performing these functions in a new host market is not evident. As such, a strong commitment to private labels may have a negative impact.

Firm size. Firm size has been described as a proxy for market power, though it may also be a source of inertia. Firm size has been associated with market power in both domestic and international contexts (Gaba, Pan, and Ungson 2002). Large firms may identify more time-dependent opportunities. For example, they are better able to make preemptive moves that limit later entrants from access to suppliers, markets, customers, and other scarce resources and are more likely to have stronger bargaining power to gain concessions from the host-country government. Finally, they tend to have more financial resources, which provide a buffer against downside risks. In contrast, bureaucratic tendencies arising from greater structural complexity and formalization can lead to increased rigidity. This negatively affects a retailer's ability to react quickly to changing environments or to grasp new opportunities fully. As such, larger firms may be less able to exploit time-dependent advantages (Lieberman and Montgomery 1988). Because of these opposing forces, it is difficult to predict the impact of firm size.

Host-Market Attractiveness

In assessing the impact of the aforementioned knowledge factors, it is also necessary to control for the host market's intrinsic attractiveness. We consider the impact of the distance between a potential host country and a retailer's home market, the extent to which a transition economy is opening up for new entrants, and the strength of the local players in the host market.

Home-market distance. Distance between the host market and the retailer's home market decreases the attractiveness of a new market, making it more likely that the retailer will adopt a cautious attitude. Indeed, distance determines how difficult it is to realize a knowledge transfer from home market to a potential host market. In line with the work of Mitra and Golder (2002), we consider the impact of cultural, geographic, and economic distance. Note that these distances differ between different host markets but not among retailers originating from the same home market. In contrast, the aforementioned near-market knowledge constructs can also differ among retailers from the same home country.[1]

Extent of liberalization. Although CEE economies share a common legacy of central planning, their economic liberalization did not materialize to the same extent or at the same pace (De Melo et al. 2001). The intensity of the political and economic reforms is likely to affect a transition economy's perceived attractiveness to foreign investors.

Strength locally based rivals. Apart from foreign players that are present in the host market, the strength of the local retailers may also be an inhibiting factor (Galbraight and Stiles 1983).

Methodology

Speed-of-Entry Decision

We adopt a hazard specification for the timing dimension, in which we define the entry rate at year t for retailer i (i = 1, ..., I) in country j (j = 1, ..., J) as $\lambda_{ij}(t)$:

$$\lambda_{ij}(t) = \lambda_{0j}(t)\exp[\beta X_{ij}(t)], \tag{1}$$

where $X_{ij}(t)$ represents a vector of time-varying covariates; $\lambda_{0j}(t)$ is the baseline hazard in j, which represents the entry rate assuming all covariates equal to zero; and β represents the vector of parameters. Estimation is based on the partial likelihood. For country j, this function becomes

$$L_j = \prod_{i=1}^{I}\left\{\frac{\exp[\beta X_{ij}(t_{ij})]}{\sum_{l=1}^{I} Y_{lj}\exp[\beta X_{lj}(t_{ij})]}\right\}^{c_{ij}}, \tag{2}$$

where c_{ij} equals one (zero) for completed (censored) observations. Its use excludes from the numerator retailers that did not experience an entry event into country j by the end of the observation period. For firms that experienced an event at a specific time (t_{ij}), we consider the likelihood that the event happened to firm i rather than to one of the other firms still "at risk" (i.e., those that can still enter). To determine the relevant risk set, we create a set of indicator variables Y_{lj}, where $Y_{lj} = 1$ if $t_{lj} \geq t_{ij}$ and $Y_{lj} = 0$ if $t_{lj} < t_{ij}$. In doing so, we concentrate on the order in which the various events take place (Allison 1984). Note that even though censored observations are excluded from the numerator in Equation 2, they can appear in the risk set composition of the denominator. A key advantage of the approach is that it does not require a distributional specification for the baseline hazard, because it no longer appears in Equation 2.

When considering the entry process across J markets, we combine the various partial likelihood expressions; that is,

$$L = \prod_{j=1}^{J} L_j = \prod_{j=1}^{J}\prod_{i=1}^{I}\left\{\frac{\exp[\beta X_{ij}(t_{ij})]}{\sum_{l=1}^{I} Y_{lj}\exp[\beta X_{lj}(t_{ij})]}\right\}^{c_{ij}}. \tag{3}$$

We assume a common set of βs across the various countries. Still, the risk set (and, thus, the relevant order of occurrence of the various events) is defined on a country-by-country basis. This procedure is known as a stratified proportional Cox approach, which no longer assumes that all observations (across the various countries) are independent but only that the observations are conditionally independent within a given country or stratum.

Size-of-Entry Decision

When entry occurred for retailer i in country j in the observation span, we record the number of stores z_{ij} opened in the initial year of entry. To account for the discrete nature of these data, we adopt a Poisson regression model. Specifically, we assume that each z_{ij} is drawn from a Poisson distribution with parameter γ_{ij}, implying that

$$P(Z_{ij} = z_{ij}) = \frac{\left(e^{-\gamma_{ij}}\gamma_{ij}^{z_{ij}}\right)}{z_{ij}!}. \tag{4}$$

Covariates can be included by specifying γ_{ij} as

$$\gamma_{ij} = \exp(cY_{ij}), \tag{5}$$

---

[1] We consider both near-market knowledge and distance relative to the home market for two reasons. First, for the initial move into CEE, no near-market knowledge from prior experiences in the emerging economies of CEE is available, whereas the distance to the home country is likely to affect the perceived attractiveness of the potential host markets. Second, even when a firm has developed near-market knowledge from other entries into the region, the distance relative to its headquarters and its most familiar home market may remain key drivers for its further expansion.

where Y_{ij} is a vector of covariates and c is the vector of parameters to be estimated. The size decision is implemented only if entry actually occurred, implying that the distribution of responses is truncated above zero (Bucklin, Gupta, and Siddarth 1998):

$$(6) \qquad P(Z_{ij} = z_{ij} | Z_{ij} > 0) = \frac{P(Z_{ij} = z_{ij})}{1 - P(Z_{ij} = 0)} = \frac{(e^{-\gamma_{ij}} \gamma_{ij}^{z_{ij}})}{z_{ij}!(1 - e^{-\gamma_{ij}})}.$$

To account for correlations within host countries, we use a generalized estimating equations approach (Liang and Zeger 1986), which has been shown to be robust to covariance structure misspecifications.

Relationship Between Entry-Timing and -Size Decisions

We adopt a recursive approach and assume that the size decision is dependent on the timing decision. Therefore, we add the year of entry as an additional variable in the Poisson model. As such, we model the dependence between the timing and the size decision by including an observable covariate (time of entry) in the size equation, which is comparable to the linkage in Dekimpe, Parker, and Sarvary's (2000) coupled-hazard approach. This ensures that the likelihood function becomes separable, allowing a separate estimation of both processes.[2] This sequential approach is based on the argument that entry decisions can be considered lumpy investments, which are discrete and occasional events. The level of such an investment decision tends to be made after the decision to invest has been made, as Bar-Ilan and Strange (1999) argue.

In terms of the expected sign of this relationship, we can posit two arguments. First, early entrants may prefer large-scale entry because this may expand the size of the market, send signals of commitment, and deter duplication (Ghemawat 1991). This suggests that there is a negative relationship between size and timing of entry. However, a positive relationship could also be posited. If a firm enters early, the risk of not recovering overhead costs may be substantial, and greater commitment implies greater risk. These risks can be substantial if the host market is in an early stage of development, suggesting a more limited scale when entering early, all else being equal.

Data

We traced 75 European grocery retailers' behavior with respect to their entry into 11 CEE markets (Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Slovakia, and Slovenia) from 1989 to 2002, resulting in 825 retailer–market combinations. We included retailers in the sample if they were listed among the 75 largest grocery retailers in Europe, based on total consolidated food sales in 1991. In total, we included retailers from 14 countries.[3] Approximately 60% of the retailers were primarily operating supermarkets, and hypermarkets and discount operations were the dominant format in 24% and 16% of all cases.

We selected Western European retailers because they are the front-runners in the globalization of grocery retailing (Organisation for Economic Co-operation and Development 2000). We considered all entries through greenfield expansion and acquisition, and we also included joint ventures. We used a historic perspective (Golder and Tellis 1993) to gather information about entries that were abandoned by the end of the observation period. We obtained the information by sequentially checking all M+M Planet Retail publications and various other trade publications.

The selection of CEE as the target market offers various advantages. First, the fall of the Berlin Wall is a natural starting point for the timing decision. Because no modern retailing was present in the target market, we can test the impact of the different drivers in a tabula rasa situation. Second, because the various markets opened to all retailers at the same time, we expect that few confounding effects are present. Finally, transition economies provide an ideal setting to assess the impact of learning derived from competitors because the countries are characterized by a substantial amount of environmental uncertainty (Luo and Peng 1999). We obtained data on market entries, competitive actions, and firm characteristics from M+M Planet Retail. Data for the distance measures come from different sources, including the World Bank and Hofstede (2001).

Dependent Variable: Timing of Entry

For every retailer–country combination, we recorded whether the market was entered. If entry took place, we measured timing as the number of years elapsed between the opening of the market (1990) and the entry date.[4] We can censor observations for two reasons. First, it could be that no entry occurred by the end of the observation period (December 2002). If this is the case, we can capture timing as the number of years (13) elapsed between the opening of the market and the end date. Second, in a few instances, a retail firm was taken over. In this case, we used the date of acquisition as the censoring date.[5] A total of 42 firms entered one or more Eastern European markets. Of those, 14 entered only one host market, 20 entered between two and five countries, and 8 entered more than five markets. The total number of recorded entries amounts to 125, which represents a hit rate of 15.1%. The median time until entry for noncensored observations is six years. Moreover, we observed variability across host markets. The most popular markets were Poland (27 entries) and the Czech Republic (18), and the least popular destinations were Bulgaria (4) and Lithuania (5). Approximately 50% of the 46 supermarket players in the sample entered at least one CEE country, as did more than 60% of the discount and hypermarket retailers in our sample.

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[2] We leave any corrections for unobserved heterogeneity for further research.

[3] Specifically, firms originated from Austria (4), Belgium (4), Denmark (2), Finland (4), France (11), Germany (14), Italy (3), Norway (4), Portugal (2), Spain (3), Switzerland (4), Sweden (3), the Netherlands (4), and the United Kingdom (13).

[4] Because the Berlin Wall fell in November 1989, we took 1990 as the first year in which entry could actually take place.

[5] Retailers that were taken over are censored before the end of the observation window. We deleted them from the set of "retailers still at risk" (the denominator of Equation 2) as soon as the timing of a particular entry exceeded the time of acquisition.

Dependent Variable: Size of Entry

We define the size of entry as the number of outlets opened in the first year. We adopt this measure because multiple outlets are needed in local-service industries to build a close-contact relationship with prospective consumers (Fuentelsaz, Gomez, and Polo 2002). Initial entry size varied considerably (range = 1–63) with a mean value of 4.4, and 38% of all entries happened through a single store. In 32% of the cases, 2–5 outlets were opened, and another 15% entered with 6–10 stores. The remaining 15% penetrated the market with more than 10 outlets.

Explanatory Variables

All explanatory variables are time varying, and we measured them at an annual level of temporal aggregation. Following the work of Steenkamp, Ter Hofstede, and Wedel (1999), we mean-centered all explanatory variables within countries. This ensures that differences in the mean levels between countries do not affect our hypothesis testing.

Interretailer information: competitive presence. For the timing decision, we measured competitive presence as the fraction of a certain subset of competitors that is present at a given point in time. We operationalized the presence of home-country players as the ratio of the number of prior entries (i.e., at the end of the year before entry) of home-market players to the number of major home players. We define major players as firms that have a market share that exceeds 1% in their home country. We express this presence in relative rather than absolute terms to correct for differences in the number of rivals present in the home market. For example, the German retailer Rewe entered the Czech market in 1996. At the time of entry in this new host market, Rewe encountered its German rivals Norma, Tengelmann, and Edeka, which entered in 1991, 1992, and 1993, respectively. In its German home market, Rewe encountered 14 major rivals. Consequently, the proportion of home-based rivals present in the Czech market was 0% until 1991, 7% in 1992 (1/14), 14% in 1993 (2/14), and 21% (3/14) from 1994 to 1996. We define the proportion of foreign players in the host market at time t in a similar way. In terms of Rewe's move into the Czech Republic, six foreign players were present before 1996. In the 13 home countries represented in our sample (other than Germany), 80 retailers had a home share that exceeded 1%. As such, the proportion of foreign players that Rewe encountered in the Czech Republic was 7.5% (6/80). To test for the incremental effect of pioneering firms, we added four step dummies to the hazard model, which take the value of one when the first home, foreign, same-format, and different-format rival entered, respectively.

With respect to the size decision, we operationalized competitive presence in terms of the average number of stores already operated by (a subset of) prior entrants. This reflects the extent of their commitment, which may be more informative than the mere presence of competitors when a firm is deciding on its own commitment level. In 1996, Rewe was confronted with 41 outlets operated by its three German rivals in the Czech republic (13.6 outlets per home player) and 220 stores run by six foreign competitors (36.6 outlets per foreign player).

Likewise, we operationalized the presence of same-format players as the proportion of same-format retailers that entered a particular host market. We distinguish among three key formats: conventional supermarkets (characterized by a hi-lo pricing strategy, broad assortment, and considerable service), discounters (everyday low prices, narrow assortments, and limited service), and hypermarkets (a pricing strategy in between the two others, a wide assortment, and intermediate service). We assigned retailers to these categories on the basis of the percentage of the parent firm's worldwide sales realized through that format (for a similar practice, see Gielens and Dekimpe 2001). We define the presence of different-format retailers in a similar way.

Finally, we added four dummy variables to the size equation to indicate whether at least one retailer of a particular type was already present in the year preceding that retailer's entry. Table 1 presents an overview of the competitive presence at three points in time.

Intraretailer Information: Firm Resources

Worldwide experience in period t is expressed as the cumulative number of international markets a firm entered by the end of the previous year (see Tan and Vertinsky 1996). We define its regional equivalent as the number of outlets opened throughout CEE by a given retail firm, again by the end of the previous year (see Li 1994). We use the number of outlets because this better captures the advantages of having a logistic network in the region.

Following the work of Mitra and Golder (2002), our measure for near-market cultural knowledge takes into account that this knowledge will increase when a retailer is active in markets that are culturally more similar to the potential host market than to its home market. Moreover, the duration of experience in each of these markets also increases the extent of cultural knowledge, but with diminishing returns. Formally, we write this measure as

$$\sum_{i=1}^{n_t} \frac{\log(1+\text{years}_{it})}{(\text{similar}_i - \text{potential})},$$

where n_t captures the number of markets in which a retailer operates at time t that are culturally more similar to the potential host market than to the retailer's home market; years_{it} expresses the number of years in market i at time t; and $(\text{similar}_i - \text{potential})$ reflects Kogut and Singh's (1988) composite measure of cultural distance, which they derive from Hofstede's (2001) data on four cultural dimensions (individualism, uncertainty avoidance, power distance, and masculinity).

In a similar vein, we define four measures of near-market economic knowledge that capture the economic similarity between each potential host market and the other (economically more similar) CEE countries in which the firm already operates: (1) economic prosperity, (2) economic size, (3) economic accessibility, and (4) economic infrastructure. These dimensions are reflected in gross national product per capita, gross national product, popula-

TABLE 1
Competitive Action Descriptives

A: Proportion of Players Present (%)

	Home Players			Foreign Players			Same Format			Different Format		
	1991	1996	2001	1991	1996	2001	1991	1996	2001	1991	1996	2001
Bulgaria	0	0	8	0	0	6	0	0	4	0	0	6
Czech Republic	4	23	41	4	19	28	4	17	24	2	24	34
Estonia	0	6	9	0	7	15	0	7	11	0	14	25
Hungary	5	17	26	6	13	21	5	12	17	4	17	26
Latvia	0	0	9	0	0	10	0	0	13	0	0	9
Lithuania	0	0	13	0	0	13	0	0	8	0	0	8
Poland	4	39	60	3	25	49	1	25	37	3	30	41
Romania	0	3	18	0	1	13	0	1	13	0	2	12
Russia	0	0	20	0	0	13	0	0	12	0	0	15
Slovakia	0	6	23	0	6	17	0	5	15	0	6	18
Slovenia	0	5	16	0	1	10	0	1	8	0	9	26

B: Average Number of Outlets per Player

	Home Players			Foreign Players			Same Format			Different Format		
	1991	1996	2001	1991	1996	2001	1991	1996	2001	1991	1996	2001
Bulgaria	.0	.0	1.2	.0	.0	4.4	.0	.0	3.1	.0	.0	4.5
Czech Republic	1.3	12.2	21.9	1.7	23.1	49.1	1.0	23.5	53.2	1.6	19.2	41.4
Estonia	.0	.1	2.9	.0	.2	10.0	.0	1.4	14.3	.0	1.19	9.1
Hungary	1.3	26.7	35.3	7.8	54.2	53.2	3.8	59.4	53.2	12.5	48.3	53.0
Latvia	.0	.0	1.0	.0	.0	6.2	.0	.0	4.9	.0	.0	7.9
Lithuania	.0	.0	1.5	.0	.0	12.8	.0	.0	9.5	.0	.0	10.2
Poland	.4	11.6	49.5	3.9	14.9	72.7	4.3	11.3	63.9	1.4	16.5	95.8
Romania	.0	1.2	3.5	.0	.8	6.4	.0	1.0	4.8	.0	1.0	8.4
Russia	.0	.0	.3	.0	.0	.5	.0	.0	1.3	.0	.0	1.3
Slovakia	1.2	6.6	17.2	2.8	32.3	51.1	.0	2.7	12.2	.0	3.1	12.2
Slovenia	1.3	1.4	2.6	1.0	5.6	4.8	1.6	3.3	5.5	1.4	1.7	2.4

tion density, and kilometers of roads per square kilometer, respectively. However, unlike the near-market cultural knowledge, we now take the absolute value of (similar_i – potential) in the denominator of the expression (for a similar practice, see Mitra and Golder 2002).

Control Variables

The annual private-label share in the retailer's home market measures the extent to which the retailer depends on private labels in its home market (Gielens and Dekimpe 2001). To capture size effects, we recorded consolidated deflated sales. We measured cultural distance between the retailer's home market and a host market in terms of Kogut and Singh's (1998) composite index. We captured geographic distance in two ways: with a dummy variable that indicates whether the retailer has its headquarters in a country that neighbors the potential host market and through the distance in miles between the host-market capital and the capital of the retailer's home market (Gielens and Dekimpe 2001). We created four economic distance measures (economic prosperity distance, economic size distance, economic infrastructure distance, and economic accessibility distance) using the four previously discussed economic attractiveness indicators. Each measure is the absolute value of the difference between the corresponding economic attractiveness variable for the home market and the potential host market. To capture the extent of liberalization, we used a measure developed by the World Bank that reflects the extent of (1) liberalization of domestic prices and the abolition of state trading monopolies, (2) liberalization of the foreign trade regime, and (3) privatization of small- and large-scale enterprises (De Melo et al. 2001). The index ranges from 0 ("unreformed") to 10 ("entirely reformed"). Finally, we controlled for the strength of local retailers by considering the number of local players that had a market share in excess of 1% in any given year.

Results

Table 2 reports the unstandardized parameter estimates and their associated t-values. Given the directional nature of most of our hypotheses, we use one-sided tests, except for the impact of firm size and, in the size equation, the impact of the timing covariate.

Interretailer Information: Competitive Actions

As we indicated previously, two opposing forces, imitation and deterrence, may be at work. A priori, it is difficult to predict which of these two forces will prevail at what range of competitive activity. As such, we specified a quadratic relationship to allow for the flexibility to incorporate (inverted) U, as well as monotonically increasing/decreasing relationships between competitive activity and the speed and size of entry. We found this flexibility to be appropriate

TABLE 2
Parameter Estimates

	Speed of Entry		Size of Entry	
	β	|t-Value|	γ	|t-Value|
Interretailer Information				
•Home-based players (β_1, γ_1)	.938	3.83***	.016	5.16***
Home-based players² (β_2, γ_2)	–.418	2.07**	–.000	2.30**
First home-based entrant (β_3, γ_3)	.171	1.19	–.372	.96
•Foreign players (β_4, γ_4)	1.003	3.83***	.113	4.31***
Foreign players² (β_5, γ_5)	–1.075	1.99**	–.018	1.82**
First foreign entrant (β_6, γ_6)	–.766	.98	–.248	.82
•Same-format players (β_7, γ_7)	.209	4.94***	.126	2.83***
Same-format players² (β_8, γ_8)	–.433	2.47***	–.006	3.01***
First same-format entrant (β_9, γ_9)	.885	1.78**	.778	2.97***
•Different-format players (β_{10}, γ_{10})	.209	2.75***	.073	2.01**
Different-format players² (β_{11}, γ_{11})	1.233	.75	–.004	5.71***
First different-format entrant (β_{12}, γ_{12})	.126	.13	–.179	.49
Intraretailer Information				
•Relevance of international experience				
Near-market cultural knowledge (β_{13}, γ_{13})	.037	1.85**	.067	2.33***
Near-market economic knowledge				
-Size (β_{14}, γ_{14})	.217	1.91**	.089	1.58
-Infrastructure (β_{15}, γ_{15})	.004	1.56	.007	1.21
-Accessibility (β_{16}, γ_{16})	.772	1.59	.774	2.43***
-Prosperity (β_{17}, γ_{17})	.000	.59	.000	2.47***
•Extent of international experience				
Regional experience (β_{18}, γ_{18})	.004	3.80***	.006	5.05***
Worldwide experience (β_{19}, γ_{19})	.076	2.74***	–.083	2.02**
Control Variables				
•Firm characteristics				
Private-label share (β_{20}, γ_{20})	–.009	2.13**	–.014	2.94***
Firm size (β_{21}, γ_{21})	.000	.37	.000	.91
•Host-market attractiveness				
Cultural distance (β_{22}, γ_{22})	–.072	1.30	–.418	2.23**
Geographic distance				
-Distance between capitals (β_{23}, γ_{23})	–.001	3.34***	–.000	1.96**
-Neighbor (β_{24}, γ_{24})	.503	1.53	.239	.80
Economic distance				
-Size (β_{25}, γ_{25})	–.001	1.89**	–.001	1.56
-Infrastructure (β_{26}, γ_{26})	–.017	1.21	–.176	1.45
-Accessibility (β_{27}, γ_{27})	–.004	1.78**	–.003	3.04***
-Prosperity (β_{28}, γ_{28})	–.001	4.17***	–.000	4.90***
Liberalization index (β_{29}, γ_{29})	.010	.11	.442	1.82**
Local players (β_{30}, γ_{30})	–.024	.17	.045	.071
Timing (γ_{31})			–.244	1.98*

*$p < .05$ (two-sided).
**$p < .05$ (one-sided).
***$p < .01$ (one-sided)

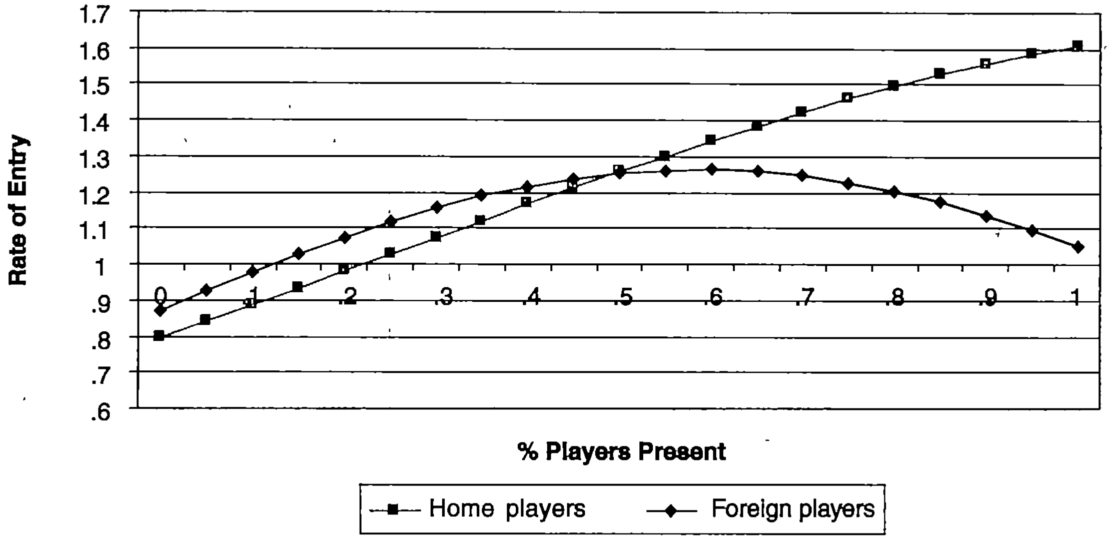
because seven of eight quadratic terms were negative and significant.

Speed of entry. We observed three of these inverted U-shaped patterns for speed of entry. We found a curvilinear relationship between the proportion of home players present in the host market and the speed of entry, as illustrated by the positive, significant linear ($\beta_1 = .938$, $p < .01$) and the negative, significant quadratic ($\beta_2 = -.418$, $p < .05$) parameter estimates. Likewise, we found an inverted U-shaped effect for the impact of foreign rivals ($\beta_4 = 1.003$, $p < .01$; $\beta_5 = -1.075$, $p < .05$). Entries made by same-format players into the host market were also curvilinearly related to the speed-of-entry decision ($\beta_7 = .209$, $p < .01$; $\beta_8 = -.433$, $p < .05$). With respect to the proportion of different-format players, we found a positive, significant linear term; the quadratic term did not reach statistical significance ($\beta_{10} = .209$, $p < .01$; $\beta_{11} = 1.233$, $p > .05$).

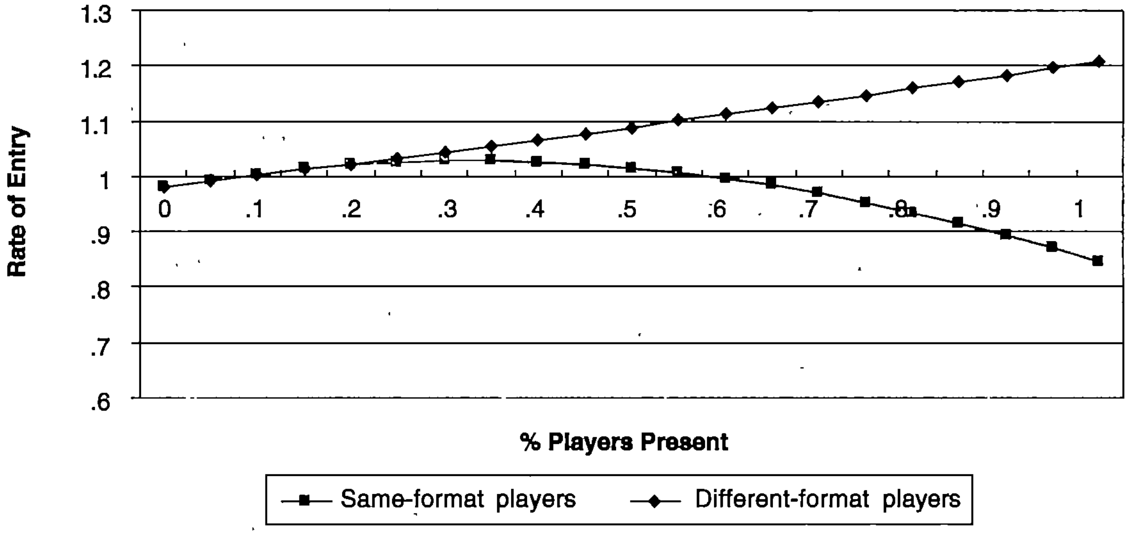
To understand these effects better, we illustrate in Figure 2 how the presence of rival retailers affected the speed of entry into the Czech Republic in 1997. Although the gen-

FIGURE 2
The Impact of Rivals' Presence on Entry Timing

A: Home Versus Foreign Players



A: Same- Versus Different-Format Players



Notes: Panels A and B depict how the presence of rival retailers affected the speed of entry into the Czech Republic in 1997. The horizontal axis represents the proportion of rivals present, and the rate of entry is given on the vertical axis. We present the results relative to the average within a country.

eral inverted U-shaped pattern would hold for other host markets and/or periods, differences in the location of the point at which deterrence effects begin to dominate the imitation/legitimization effect could be observed in other settings. Indeed, all covariates were mean-centered, and these means can change over time and countries. The horizontal axis represents the proportion of rival players that are present, and the vertical axis represents the rate of entry (speed decision). Because the independent variables were mean centered, we present our results relative to the average within a country. Figure 2, Panel A, focuses on the presence of home versus foreign rivals, and Figure 2, Panel B, considers same- versus different-format competition.

In 1997, German retailers that wanted to enter the Czech Republic observed that 56% of their key domestic rivals were already active in that market. At that point, the mean level of domestic rivals present in the Czech Republic amounted to 23%. As a consequence, the entry rate for German retailers was approximately 30% (i.e., $\exp[.938 \times \{.56 - .23\} - .418\{.56 - .23\}^2]$) higher than that for retailers with an average proportion of domestic rivals in that market. At that point, French retailers encountered only 10% of their domestic rivals in the Czech market. Their entry rate was 12% lower than that for retailers that encountered an average fraction of domestic rivals.

However, note that even though the quadratic term is negative and significant for actions by home-based rivals (i.e., –.418), we still observe a monotonically increasing pattern over the relevant data range (0–1). Thus, the learning or imitation effect from an additional entry by a home rival dominates its potential deterring effects. Still, the latter causes the net effect to level off as ever-higher fractions of home rivals are present. This deterrence effect becomes much more prevalent when the impact of entries by foreign rivals is considered. With respect to the speed-of-entry decision, we even find that after the proportion exceeds 59%, the imitation effect from an additional entry into the Czech Republic becomes outweighed by its deterrence effect.

For effect of same-format rivals (Figure 2, Panel B), the corresponding curve is again curvilinear. Specifically, when approximately 35% of the same-format rivals are present, the deterrence effect begins to outweigh the legitimization effect. In contrast, the impact of additional different-format players is positive over the entire range. Because different-format players compete less directly for the same consumers, their presence is considered a good indicator of the opportunities in the host market, while being less threatening. The country-of-origin effect seems to be more pronounced than the format effect because the curves that depict the latter tend to be flatter, resulting in a smaller effect size over the relevant data range. With respect to the incremental impact of the first entrant, we find evidence of such an effect for the same-format pioneer ($\beta_9 = .885$, $p < .05$) but not for the first home-based, foreign, or different-format player ($\beta_3 = .171$, $p > .05$; $\beta_6 = -.766$, $p > .05$; $\beta_{12} = .126$, $p > .05$).

Size of entry. With respect to size, we found four curvilinear effects. There is an inverted U-shaped effect for both home-based rivals ($\gamma_1 = .016$, $p < .01$; $\gamma_2 = -.0001$, $p < .05$) and foreign players ($\gamma_4 = .113$, $p < .01$; $\gamma_5 = -.018$, $p < .05$) that are present in the host market. Likewise, for both format groups, we found an inverted U shape (same-format players: $\gamma_7 = .126$, $p < .01$; $\gamma_8 = -.006$, $p < .01$; different-format players: $\gamma_{10} = .073$, $p < .05$; $\gamma_{11} = -.004$, $p < .01$). Notably, although we found that same-format presence quickly started to deter entry, when the entry decision was made, retailers initially derived a net positive impact from additional same-format stores. With respect to the timing decision, we again observed an incremental effect of the first same-format rival on the size of entry ($\gamma_9 = .778$, $p < .01$). All else being equal (i.e., setting all other covariates at the host country's mean in a given year), we can show that the first retailer of a particular home country is expected to enter with three stores when home-market players operate, on average, five stores in that host country (Cameron and Trivedi 1998). This number is below Kumar's (1997) minimum efficient scale. However, if the retailer encounters home rivals that already operate 25 stores, this expected level of initial commitment increases to six stores, implying entrance at minimum efficient scale.

Intraretailer Information

Speed of entry. As we expected, a higher level of near-market cultural knowledge increases the speed of entry in a new potential host market ($\beta_{13} = .037$, $p < .05$). Likewise, more near-market size knowledge ($\beta_{14} = .217$, $p < .05$) positively affects the speed of entry. Furthermore, more international experience, both regional and worldwide, increases the speed of entry ($\beta_{18} = .004$, $p < .01$; $\beta_{19} = .076$, $p < .01$).

Size of entry. In line with our hypotheses, we find that near-market cultural knowledge increases the number of stores opened ($\gamma_{13} = .067$, $p < .01$). Moreover, near-market economic knowledge positively affects the size decision; we found a positive, significant effect for two of the underlying similarity dimensions: accessibility ($\gamma_{16} = .774$, $p < .01$) and prosperity ($\gamma_{17} = .00002$, $p < .01$). Regional experience has a positive effect on the size decision ($\gamma_{18} = .006$, $p < .01$). However, contrary to prior expectations, more global diversity results in less stores being opened at the time of entry ($\gamma_{19} = -.083$, $p < .05$). If a retailer operates in many markets, its resources become more thinly spread, thus hampering a large-scale entry into each market. In contrast, regional experience ensures the necessary logistic support to open more stores in the region.

Control Variables

Speed of entry. As we predicted, the share of private labels in the assortment negatively influences the speed decision ($\beta_{20} = -.009$, $p < .05$). The impact of firm size was not significant. We found no support for the expected negative effect of cultural distance on speed of entry ($\beta_{22} = -.072$, $p > .05$). However, the speed of entry decreases significantly with the distance between capitals ($\beta_{23} = -.001$, $p < .01$), but we found no additional neighboring effect ($\beta_{24} = .503$, $p > .05$). We found that the speed of entry is lower in markets characterized by economic conditions that are different from the home market in terms of size, accessibility, and prosperity ($\beta_{25} = -.001$, $p < .05$; $\beta_{27} = -.004$, $p < .05$; $\beta_{28} = -.001$, $p < .01$). In contrast, we found no significant effect for infrastructure distance, the extent of economic liberalization, or the strength of the local players.

Size of entry. As for the timing decision, private-label share negatively influences the size decision ($\gamma_{20} = -.014$, $p < .01$), whereas again, the impact of firm size does not reach statistical significance ($\gamma_{20} = .000$, $p > .05$). In contrast to the speed of entry, we found that fewer outlets are opened at the time of entry as the cultural distance ($\gamma_{22} = -.418$, $p < .05$) and the distance between the respective capitals ($\gamma_{23} = -.00002$, $p < .05$) increase. However, we observed no neighboring effect with respect to the size decision ($\gamma_{24} = .239$, $p > .05$). Moreover, the size decision is negatively influenced by two economic distance measures between host and home market ($\gamma_{27} = -.003$, $p < .01$; $\gamma_{28} = -.0001$, $p < .01$). Different from the speed of entry, the size decision is positively influenced by the extent of liberalization in the potential host country ($\gamma_{29} = .442$, $p < .05$). Locally based players did not play a major role in the size-of-entry decision ($\gamma_{30} = .045, p > .05$). Finally, as discussed in the "Methodology" section, we included the timing variable in the size equation. We found a negative, significant effect ($\gamma_{31} = -.244, p < .05$ [two-sided test]).

Validation

To assess the robustness of our results, we explored whether our results pertaining to the nature of interorganizational learning (1) hold for both more and less liberalized transition economies, (2) are sensitive to the operationalization adopted for the competitive action measures, (3) are sensitive to our treatment of firms taken over by competitors, and (4) are sensitive to whether the first entrant of a certain type is excluded from the analyses.[6]

Testing for Differences Between More and Less Liberalized Regions

For the timing decision, we implemented a split-sample analysis, in which we checked whether similar substantive implications held for both more and less liberalized transition economies. Because of the more limited sample size for the count model (n = 125), we did not implement any such split-sample analysis for the size decision. We identified two groups, in line with a dichotomy proposed by the World Bank (De Melo et al. 2001): We labeled Poland, Slovenia, Hungary, the Czech Republic, and the Slovak Republic as "advanced reformers" and Bulgaria, Estonia, Latvia, Lithuania, Romania, and Russia as "intermediate reformers." Our conclusions regarding the nature of the interfirm knowledge transfer, reflected in the different curvilinear patterns and the presence/absence of an incremental effect for pioneering entries, hold in both subsamples.

Sensitivity to the Operationalization of Competitive Actions

Firms may learn not only from the mere presence of their rivals but also from their rivals' performance in a potential host market. Although the number of players or the number of stores they operate is relatively easy to observe, accurate and (especially) timely information about each competitor's performance in a host market is more difficult to obtain. Still, we tried to incorporate performance information in three different ways.

First, we checked whether an additional information signal emanates from competitors' exits. We incorporated four additional exploratory variables into our models—the proportion of exits by home and foreign retailers and by same-format and different-format players—none of which had a significant impact on the timing decision. Moreover, our substantive findings pertaining to the nature of interfirm knowledge generated through competitive presence remained unaffected, the only difference being that the impact of first same-format entrants (β_9) was significant at $p = .052$ (rather than at $p < .05$). For the size decision, we obtained similar curvilinear patterns for the impact of competitive presence. However, the exit variables consistently had a significant, negative impact, as we expected ($\gamma_{\text{home exits}} = -.025, p < .01$; $\gamma_{\text{foreign exits}} = -.073, p < .05$; $\gamma_{\text{same-format exits}} = -.203, p < .01$; $\gamma_{\text{different-format exits}} = -.065, p < .05$). In combination, these results confirm that firms consider the presence of other players when deciding on entry timing and size and become even more cautious to commit substantial resources when some of the players in the reference group exit.

Second, we acknowledge that incumbent expansion/disinvestment may also offer a useful performance signal. Therefore, we took only (stores operated by) those retailers into account that did not reduce their number of outlets the previous year. Again, this did not affect our substantive insights into the presence of legitimization/deterrence effects.

Third, Kumar (1997) argues that a retailer can operate successfully in a new host market only if its operations exceed a certain minimum efficient scale. Kumar estimates that this is obtained if a retailer is present with at least six to eight outlets. Following this suggestion, we used a minimum of six outlets as a cutoff value and recoded all data in such a way that as long as retailers had fewer than six outlets, they were not yet accounted for when computing the extent of competitive presence. Our substantive insights into the nature of interfirm competition were not affected, the only difference being that γ_2 had a p value of .054.

Sensitivity to the Treatment of Takeovers

In some instances, a firm was taken over, in which case we used the acquisition date as the censoring date. For such firms, we could no longer enter the numerator of Equation 2 from that period onward. For example, as soon as the French retailer Promodès was taken over by Carrefour in 1999, it was no longer "actively present" in the sample. Moreover, the acquiring retailer can change dramatically in private-label share and size. We tested whether such changes in sample composition affected our results. We considered two alternative treatments of takeover operations. First, we removed all firms involved in an acquisition operation (either as the firm that was taken over or as the firm taking over another retailer). Second, we considered the merged retailers as if they were a single entity from the beginning of the observation window; that is, we removed only the firm that was taken over from the sample, and we immediately adjusted the size of the firm taking over the other retailer. Again, our substantive insights were robust.[7]

Sensitivity to the Treatment of First Entrants

Because pioneers may perceive different opportunities and/or risks, somewhat different processes may be at work. We allowed for a differential legitimization/deterrence effect of the first entrants through the inclusion of four indicator variables. As a final validation exercise, we estimated the size and timing model on a reduced sample, in which we excluded each country's first entrant and defined the entry timing relative to that pioneer rather than to the fall of the Berlin Wall. Again, our substantive insights into the nature of interorganizational learning were robust.

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[6] Full details on these validation exercises are available on request.

[7] The only difference was that three parameters were significant at $p < .06$ (rather than at .05).

Discussion

A key issue that managers face when formulating an entry strategy is to define the competitive arena—that is, to identify the competitors and assess the likely intensity of their presence (Day 1997). In this article, we derived an industry model that describes Europe's top 75 retail chains' choices of entry into the emerging markets of CEE in terms of timing and size. We derived various theory-based expectations about the antecedents of these decisions, which are largely supported by our empirical findings. This suggests the presence of a certain amount of rationality in these retailers' decision making (Steenkamp et al. 2005), and it shows that it is possible to predict the type of competitors a firm is likely to face at the time of entry (Fuentelsaz, Gomez, and Polo 2002).

Learning from Industry Wisdom

We find substantial evidence for the existence of interorganizational learning. Faced with the considerable uncertainty surrounding entry decisions in markets that only recently opened their borders, managers consider prevailing practices in the industry to guide their own decisions. Moves made by the home rivals are followed especially closely. Rivals' presence reduces perceived uncertainty because firms with similar backgrounds have already made the move. For example, France's Auchan cites the presence of its French rivals Leclerc and Casino as a key driver to also enter Poland (*Polish News Bulletin* 2000). It also explains the emergence of national clusters in the early stages of the internationalization into CEE.

However, foreign players are not ignored. Notably, the deterrence effect of their presence is found to be much more prominent. There is anecdotal support for this in Carrefour's announcement to postpone its Hungarian expansion in favor of Romania and China to avoid competition with chains such as the United Kingdom's Tesco or Germany's Metro (*Grocer* 2000).

Learning and deterrence is also derived from format-based reference groups. The first same-format player to enter a new CEE market clearly sends a positive signal. However, because same-format entries compete directly for the same consumers, they tend to exert a deterrent effect on the timing decision. In contrast, different-format entries accelerate the own entry decision. Although different-format entries are informative about the market potential, they are perceived as less threatening. Still, after retailers have made the decision to enter, the commitment level of their same-format rivals provides relevant information about how the retail concept is accepted. Previous studies show that managers tend to ignore competition when making routine (e.g., promotional) decisions in stable environments (Steenkamp et al. 2005). Our findings indicate that they are less inclined to do so when making more strategic decisions in uncertain conditions.

Apart from the interorganizational learning derived from observing competitors' moves, intraorganizational learning is also relevant because both global and regional experiences, as well as near-market cultural and economic knowledge, are organizational factors that explain international expansion into emerging markets. Moreover, as retailers enter many different countries at a fast pace, it becomes more difficult to allocate considerable resources to each of them.

Retailers with a large private-label share in their home market tend to be later, smaller-scale entrants. On the demand side, matching new customers' assortment preferences may take longer when private labels substitute for the better-known and, in the case of emerging markets, long-expected (inter)national brands. On the supply side, a reliance on private labels as in the home market may entail drastic and time-consuming investments in the target country. For example, Tesco needed to convince its private-label suppliers to set up offices in CEE to avoid the costly need to ship these goods from its U.K. home base (Benady 1997). Retailers can respond to the growing saturation in their home market by diversifying along two dimensions: across product boundaries (e.g., by adding new lines to its private-label program) or across market boundaries (by entering new countries). Our findings suggest a trade-off between both options.

The strong impact from rivals might be interpreted as supporting the view that in their rush to internationalize, retailers are motivated less by the chance of creating value in these new markets than by their fear of being left out by their competitors. Still, economic considerations are not ignored, because negative effects are found for most economic difference variables.

Finally, we find that firms that enter late open a smaller number of stores in their initial year. Gielens and Dekimpe (2001, p. 236) study whether it is better for retailers to "quickly enter a market on a more limited scale, or to postpone entry until more resources have accumulated to enable a large-scale commitment." Our findings show that retailers follow a third strategy, in that firms that are cautious in their entry timing exhibit a similar constraint when deciding on their commitment level.

Improving Through Industry Wisdom

Entry decisions are infrequent and, especially in emerging markets, difficult. Managers have limited own experience with such decisions and therefore turn to prevailing practices in the industry to learn which decisions are good or even best (Anderson 1988; Geletkanycz and Hambrick 1997). As we indicated previously, competitive entry decisions are indeed monitored closely, providing a significant input in the retailers' decision processes. However, the wide variation in both the year of entry and the number of stores opened indicates that this does not imply a mere copying of the most popular (modal) pattern; rather, industry rules suggest different entry decisions contingent on external (e.g., host-market attractiveness) and internal (reflecting each firm's specific resources) conditions.

Does it pay to adhere to this "combined industry wisdom"? Do firms whose entry timing and size conform to the pattern of decision making in the industry (as captured in our descriptive models) perform better than firms that deviate from these rules? If so, are these performance premiums temporary or permanent? For which decision, timing or size, is adherence to industry practice more critical? Finally, when in doubt, is it better to be cautious and enter later with fewer stores than industry practice would prescribe, or is it better to take a bolder stance?

To answer these questions, we link postentry performance with the extent to which actual entry decisions deviate from the values prescribed by prevailing industry practice. We measure postentry performance in terms of sales efficiency (i.e., the total annual sales of the foreign subsidiary relative to the chain's total store surface in that country). We measure short-term performance three years after entry, and we operationalize long-term performance as the asymptotic performance level to which the foreign operation is converging, obtained by fitting a Gompertz growth model through the entries' performance data (for an in-depth discussion on this procedure, see Gielens and Dekimpe 2001). We link the logarithm of the absolute value of the deviations from industry practice (i.e., our model's residuals)[8] to the log of the performance measure, giving the parameters an elasticity interpretation. In deriving these elasticities, we control for various other factors, such as strategic entry decisions (e.g., size and timing of entry) and several other retailer-specific (e.g., private-label share, firm size, and international experience) and host-market-related (e.g., the extent of liberalization, geographic and cultural distance) factors that could influence postentry performance.[9]

As Table 3, Panel A, shows, deviations from prevailing industry practice, in terms of both timing and size, hurt short-term efficiency ($\eta_{SR} = -.25$, $p < .05$; $\eta_{SR} = -.17$, $p < .05$, respectively). However, the detrimental effects of entering at a different time from the industry norm persist and are even amplified in the long run ($\eta_{LR} = -.67$, $p < .05$), whereas they have only a temporary effect for size deviations ($\eta_{LR} = -.20$, $p > .05$). Thus, corrective actions are easier to implement along the size than along the timing dimension.

In Table 3, Panel B, we allow for asymmetric effects of entering slower (at a smaller scale) versus faster (at a larger scale) than industry practice prescribes. In terms of size, short-term efficiency is hurt only when the firm enters with too many stores ($\eta_{SR} = -.35$, $p < .05$), but again, this effect disappears over time ($\eta_{LR} = -.14$, $p > .05$). This suggests that corrective actions can be taken by closing some of these stores or that the firm's growth eventually justifies the higher number of stores. However, when entering faster ($\eta_{SR} = -.57$, $p < .05$) or slower ($\eta_{SR} = -.18$, $p < .05$) than industry practice would prescribe, short-term efficiency is again hurt, but only the latter effect persists over time ($\eta_{LR} = -.76$, $p < .05$). Therefore, disadvantages associated with too late of an entry prove to be difficult to reverse (Lieberman and Montgomery 1988).

Day and Reibstein (1997, p. 8) identify two strategic errors that companies often make in a dynamic business setting: "the failure to anticipate competitors' moves and the failure to recognize potential interactions over time." Our

TABLE 3
Implications of Deviations from the Industry Norm

A: Performance Implications

	Short-Term (Three-Year) Efficiency		Long-Term (Asymptotic) Efficiency	
Absolute Value Residual	η_{SR}	|t-Value|	η_{LR}	|t-Value|
Timing	–.25	2.21*	–.67	1.92*
Size	–.17	2.06*	–.20	1.01

B: Asymmetry of Performance Implications

	Short-Term (Three-Year) Efficiency		Long-Term (Asymptotic) Efficiency	
Absolute Value Residual	η_{SR}	|t-Value|	η_{LR}	|t-Value|
Timing				
Faster than predicted	–.57	1.77*	–.23	.33
Slower than predicted	–.18	1.81*	–.76	1.99*
Size				
Larger than predicted	–.35	2.14*	–.14	.21
Smaller than predicted	–.14	1.46	–.49	1.47

*$p < .05$ (one-sided).

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[8] For more technical detail, see Allison (1999).

[9] We refer to the work of Gielens and Dekimpe (2001) for the precise operationalization of these control variables. Detailed results on their impact are available on request.

descriptive model shows that it is possible to infer competitors' future entry behavior and to incorporate how they will likely react to own decisions. As such, we developed a tool for strategic competitive reasoning (Montgomery, Moore, and Urbany 2005). Moreover, we show that when firms make infrequent, strategic decisions in uncertain environments, they pay close attention to prevailing practices in their industry. This extends recent findings that managers tend to ignore competition when making routine, tactical decisions in stable environments (Steenkamp et al. 2005). However, rather than just imitating the industry's most popular or modal decisions, they follow a more intricate, contingent approach. Not only do they pay more attention to some competitors than to others, but they also adjust for the specificity of their own resources and for changed circumstances over time. Finally, we find that firms are justified to adhere closely to industry practices because both short-term (for timing and size) and long-term (for timing) performance is hurt when they deviate from the underlying industry rules. In line with the work of Fredrickson (1984) and Anderson (1988), we find that defying combined industry wisdom in volatile and uncertain settings hurts performance, suggesting that a firm's attempts to develop its own, distinct rules are likely to be dysfunctional.

Further Research and Limitations

The current study has several limitations, which offer useful areas for future research. First, our hypotheses about the impact of interorganizational learning are inspired by the density dependence model. On the basis of two underlying forces, legitimation and competition, we derived the testable proposition that the relationship between entry and density takes the form of an inverted U. As is common in the population ecology literature (see, e.g., Carroll and Hannan 2000), we did not derive distinct measures for the concepts of legitimation and competition, but we used them as underlying forces to motivate our expectations. Although this practice of deriving a testable hypothesis about the observed net outcome variable is frequently used in the marketing literature on the relationship between ad repetition and attitude toward the ad (e.g., Rethans 1986), on the effect of stress on job performance (Singh 1998), and on the satisfaction–loyalty relationship (Augustin and Sing 2005), we believe that the derivation of direct measures for the underlying processes could offer useful additional insights. For example, this would make it possible to test whether the inverted U is indeed caused by the specific slopes of these two underlying factors or whether other drivers should also be taken into account. Second, although we included several retail-specific characteristics as control variables, more work is needed to capture differences in their functional capabilities (Dutta, Narasimhan, and Rajiv 1999). Third, our sample consisted of all entries made by Western European food retailers into CEE. The question remains whether our results can be generalized to other industries. Moreover, we did not consider any cross-continental moves. These are still less frequent, quite recent, and not yet well documented. It would be worthwhile to investigate whether our findings generalize to these more distant internationalizations. For example, does the role of cultural and/or geographic distance increase when dealing with cross-continental expansions? Moreover, although Western European food retailers account for more than 90% of all international entries in the sector in the considered time span, the gradual international expansion of U.S. retailers was not reflected in our sample. Moreover, given Wal-Mart's unique position, the extent to which other U.S. retailers will perceive its presence in a particular host market in the same way they would interpret the international expansion decisions of other U.S. competitors is unclear. Indeed, Wal-Mart may be considered a reference group on its own. Finally, foreign entries reflect a lumpy investment. We did not consider subsequent growth opportunities, which involve more incremental investments. Different processes underlie these two expansion decisions (Bar-Ilan and Strange 1999), if only because different strategies are available to reduce the intrinsic uncertainty. In the case of an initial entry, no own experience into the specific target market is present within the company. Therefore, external sources of information (e.g., an observation of competitors' moves) are crucial to reduce the perceived level of uncertainty. In contrast, decisions for future growth can be driven by own experience in the market, thus allowing a more direct approach to uncertainty reduction. However, the role of other players' moves in influencing these decisions is still unclear.

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